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The impact of firm-level Covid rescue policies on productivity growth and reallocation☆

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ABSTRACT

We evaluate the impact of Covid-19 rescue policies on both firm-level and aggregate productivity growth, exit, and creative destruction. Using administrative data on the universe of firms' support mechanisms in Flanders over 2019–2021, we first estimate the causal impact of this support program on firm-level outcomes. Firms that received support saw a 4%–5% increase in productivity, compared to similar firms that applied for, but did not obtain support. The productivity premium effect is temporary however: by the last quarter of 2021, treated firms are indistinguishable from untreated firms. Support measures also drastically reduced firm failure. The propensity to exit the market was 45% lower for treated firms, and if no support would have been issued, aggregate firm exit would have increased by 9%. We decompose aggregate productivity growth, a share-weighted average of firms' productivity growth rates, into several components. Within firms over time, both treated and untreated firms contribute positively to aggregate productivity growth. There are signs of insufficient creative destruction on both the extensive margin (firm entry and exit) and intensive margin (reallocation of market shares to more productive firms) during the crisis. However, insufficient reallocation was already present well before the crisis, and there is no evidence that this inefficiency is driven by the contribution of treated firms in particular. Firm-level support measures helped firms to avoid exit, and to temporarily increase productivity, while not altering the ongoing process of creative destruction in the aggregate.

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1. Introduction

On top of a massive health crisis, the Covid-19 pandemic has led to an unprecedented drop in economic activity around the world, as GDP in most Western countries fell between five to ten percent in 2020 (World Bank, 2022). These numbers resulted from a combination of lockdown policies, industry closures, and increased uncertainty about both short- and long-term economic outlooks. To avoid a complete meltdown of the economy, many governments implemented a variety of firm-level support measures to flank the restrictive sanitary measures, including direct firm subsidies, furlough schemes, and bank guarantees (see OECD (2021) for an overview). While such measures have likely supported economic activity, government interventions might hamper the process of creative destruction, as infra-marginally productive firms remain in the market at the expense of resources that could have gone to more productive firms. As a result, such policies could unintentionally contribute to a further aggregate productivity slowdown already present in many EU countries (Andrews et al., 2016), or an increased "zombification" of the economy (Andrews et al., 2017).

In this paper, we evaluate the impact of firm support in detail. We ask the following questions: (i) "what is the impact of the Covid-19 support measures on firm-level outcomes?", and (ii) "how do these support measures affect aggregate productivity growth and creative destruction?". To answer these questions, we combine four administrative firm-level datasets for Flanders (Belgium).[1] We use data on all Flemish enterprises applying for a Covid support measure in 2020, and their outcomes from 2019 to 2021. This data contains information at the firm-application level, with the date of application, whether support was approved or not, and if granted, the payment date and amount of support. For all enterprises that applied, we combine this information with sales from their quarterly VAT declarations. For the universe of Flemish firms, i.e. also those outside the support scheme, we use information on employment in terms of full-time equivalents and the sector of economic activity from the Social Security Office. We combine these data with firm-level variables from the annual accounts at Bureau Van Dijk for the period 2005–2021.

We then estimate the causal effect of the support measures on firm-level outcomes using a difference-in-differences strategy: we compare enterprise outcomes before and after treatment (first difference) with enterprises that applied for but did not obtain support (second difference). Within firms over time, supported firms see an increase in labor productivity by 4%–5% more, relative to similar firms that did not obtain support. Exploiting the rich panel structure of the data, we also estimate the impact of the support on quarterly productivity growth. We find that labor productivity increases with 4% in the first quarter of the first support, and is persistent up to six quarters after treatment. The effect tapers off however, and washes out by the end of 2021. There is significant heterogeneity in the nature of the individual support premia, which range from lump sum to ad valorem support, and vary substantially in the total amount per premium. We therefore estimate the impact of each type of premium separately, and find that the first premium, which supported the largest number of firms, with the largest monetary support, at the beginning of the crisis, using a lump sum transfer, contributes most to the productivity effect.

We also estimate exit rates for treated versus non-treated firms. Even while aggregate exit rates were very low over this period mainly due to moratoria on bankruptcies, we find a strong and negative effect of support on exit rates: controlling for typical firm observables, treated firms have a 0.5 percentage point (p.p.), or 45% lower probability to exit the market. In the absence of firm support measures, aggregate firm exit would have been 0.1 p.p., or 9% higher. We also provide several robustness results, including a placebo test, additional controls for federal furlough schemes that might affect both treated and untreated firms, alternative control groups based on nearest neighbor matching, and the alternative estimator of Sun and Abraham (2021) to control for heterogeneous treatment effects in a pooled estimation setup. All results confirm our baseline estimates. We also perform an exact decomposition of labor productivity into sales or value added components, and the employment component. While all components decrease, employment decreases slightly more, generating a positive productivity effect.

In the second part of the paper, we turn to the implications of firm-level support measures on aggregate productivity growth. Productivity growth is often considered the main component of GDP growth (e.g. Solow, 1956, 1957; Hulten, 1978). Especially during Covid-19, there has been no direct capital destruction, further increasing the role of labor and productivity in explaining aggregate output growth (Zegel et al., 2021). We first decompose aggregate labor productivity growth into its main components, value added and labor. In 2020, both value added and labor dropped significantly. However, the drop in labor was much larger than that of value added, generating a positive productivity growth. In 2021, employment recovers, and productivity growth dampens, albeit remaining positive. We then decompose aggregate growth into four firm-level components, building on Olley and Pakes (1996) and Melitz and Polanec (2015): (i) the within-firm average growth rate of surviving firms, (ii) the change in covariance in market shares and productivity, (iii) the aggregate contribution of entering firms, and (iv) the contribution of exiting firms.

What is the total impact of the recession on creative destruction? We evaluate two margins of creative destruction: an extensive margin, which is the contribution of net entry and exit of firms, and an intensive margin, which is the reallocation of market shares towards more productive firms. Aggregate productivity growth in both 2020 and 2021 is mostly driven by the unweighted productivity of surviving firms (8.5% and 4.3% respectively), but it is attenuated by insufficient creative destruction. The reallocation term is negative in both years at −3.5% and −1% in 2020 and 2021, while the net entry effect was positive at 1% in 2020 and negative at −1.2% in 2021. Hence, there is a negative reallocation effect of market shares towards less productive firms. This might

[1] In many countries, firms could apply for rescue support to compensate for drastic lockdown measures and highly restricted economic activity. In Belgium, each of the three regions (Flanders, Brussels and Wallonia) developed and implemented separate but similar policy measures. We focus on Flanders, which accounts for 60% of Belgium's GDP, 80% of Belgium's imports and exports, and for which we obtained confidential data on the various firm-level support measures.

signal insufficient creative destruction at the level of the economy. However, the intensive margin component points to insufficient creative destruction since 2018, well before the crisis.

Building on our findings from the difference-in-differences setup, we also provide an extended decomposition that allows to further linearly separate all components across treated and non-treated firms, including all firms that did not receive support. This decomposition includes a new reallocation term between treated and non-treated firms. Within firms, both treated and untreated firms contribute to aggregate productivity growth, with 4.1% and 4.4% respectively in 2020, and 2.6% and 1.7% in 2021. Their contributions in the aggregate are similar, but as the market share of treated firms is much smaller, this suggests that treated firms contribute more on average per firm, consistent with the difference-in-differences results. These results suggest that the productivity growth of treated firms was not just a catch-up effect, but in fact treated firms contributed disproportionally more to aggregate positive productivity growth. In both treated and untreated groups, a negative reallocation persists, pointing towards insufficient creative destruction across both treated and non-treated groups. However, there is a positive reallocation effect from treated to untreated of 1.1% in 2020, with a partial reversion in 2021 of −0.4%. In other words, untreated firms have gained market share at the expense of the treated firms.

All in all, our results suggest that Covid support measures provided a temporary productivity premium to treated firms and reduced exit drastically. We discuss various potential mechanisms that can generate these results. First, while we do not have quantitative information on how firms have used the government support, we do have information from interviews with enterprises that have been supported in Flanders. Respondents mention that the support measures have mostly been used as intended: to cover fixed costs, to keep personnel, to avoid liquidity and solvency issues, and to overcome the highly uncertain periods of lockdowns and (partial) reopening of the economy. Second, we then triangulate our quantitative results with these interviews and basic economic theory. In particular, support measures can be used to strengthen solvency and liquidity positions, reducing the probability of exit. Moreover, we see that both output and employment drop, but both components drop more for treated firms than untreated firms. If firms are shut down, or see a massive reduction in demand for their goods and services, labor demand decreases. If labor is a variable cost, labor use is reduced, and treated firms might use this support to increase capital buffers, creating alternative market places such as online sales platforms etc. If labor is a fixed cost, firms can use the support measures to pay at least part of these costs. In the short run, the firm faces a shutdown decision: it operates as long as revenues are at least as large as variable costs. If not, it shuts down. When economic conditions improve, the firm might decide to open up again, and increase demand for its factors such as labor. This is also consistent with what we see in the aggregate from 2020 to 2021. In the long run, if equity cannot cover the fixed costs of production, the firm exits the market.

Are these productivity increases sustainable in the long run? There are several arguments that suggest that these productivity increases are not sustainable, such as high work pressure and evidence for high burn-out rates in 2020. Our empirical results also find that the productivity premia are temporary, and labor demand increases sharply again in 2021. Conversely, there are also some arguments in favor, including efficiency improvements from capacity utilization, sorting and selection on worker quality, and access to new markets.

There are by now several papers that have evaluated the impact of Covid-19 on firm-level outcomes. Dhyne and Duprez (2021) document the evolution and cross-sectional heterogeneity of Covid-19 on firm outcomes for Belgium. Cros et al. (2021) use French firm-level data and find that the typical mechanisms triggering bankruptcy, such as low productivity and debt, also predict firm exit during Covid-19. Tielens and Piette (2022) find similar results for Belgium. Tielens et al. (2020) and Chundakkadan et al. (2022) study the impact of capital constraints on firm-level outcomes during Covid.

A few papers have studied the impact of policy support on firm-level outcomes. Davies et al. (2023) find that support in the Netherlands reduced the overall exit rate of companies by 16% in 2020. Harasztosi et al. (2022) study the impact of support policies on firm outcomes across the EU, and find that support was not tilted towards already weak firms before the crisis, but that low liquidity firms were more likely to be supported, which subsequently raised the likelihood of increasing their equity base. Hurley et al. (2021) study the uptake of government loans by UK SMEs. Evaluating the impact of Covid and firm-level support measures on the process of creative destruction, Bighelli et al. (2021) use firm-level data for Croatia, Finland, Slovakia, and Slovenia, and show that government subsidies were distributed towards medium productive firms, and only marginally towards "zombie firms". In contrast, Freeman et al. (2021) show that Covid-19 support measures such as furlough schemes, subsidies and tax deferrals in the Netherlands distorted the process of creative destruction. In Flanders, the share of supported firms that have a negative value added in 2019 is in fact lower (9%) than the share of firms with negative value added in the economy (14%) (Zegel et al., 2021).

Our results also speak more generally to the mechanisms of creative destruction and aggregate growth. The seminal paper by Aghion and Howitt (1992) provides a dynamic framework of creative destruction in the absence of intervention, where markets can either over- or underinvest in productivity improvements. Bartelsman et al. (2004) provide a cross-country analysis of creative destruction on aggregate productivity growth, the churn of entrants and exiting firms, and the reallocation of resources towards more productive firms. Dvouletý et al. (2021) perform a EU cross-country meta-analysis of government support on firm outcomes and the process of creative destruction. They find that various flavors of government financial support measures increase firm survival, labor use, capital and sales, and/or firm productivity. Finally, Caballero and Hammour (1994, 1996) argue that there are strong reasons why an efficient economy ought to concentrate on both job creation and destruction during recessions, when the opportunity cost of reallocation is lowest.

The rest of the paper is organized as follows. In Section 2, we describe the data in detail and provide summary statistics. Section 3 reports the results of an event study in which we analyze the impact of direct support measures on productivity. Section 4 analyzes aggregate productivity growth and decomposes its channels into productivity growth. In Section 5, we discuss additional robustness exercises. Section 6 provides a discussion of interview responses and potential mechanisms. We conclude in Section 7.

2. Data and summary statistics

2.1. Data sources and construction

We combine four administrative datasets to analyze the impact of firm-level Covid support measures on productivity growth and exit at both the enterprise and aggregate levels.[2] First, we use information on all Flemish enterprises that applied for VLAIO Covid support in 2020. This dataset is confidential, and courtesy of VLAIO, the Flanders Innovation and Entrepreneurship Agency that administered and distributed these support mechanisms. The dataset contains information on each application submitted by an enterprise, with the date of application, the sector of economic activity that applies to the support mechanism, whether or not the application was approved, and if granted, the date and amount of the payment. Second, for all enterprises that applied for these Covid support measures, we obtain quarterly information on sales from the first quarter of 2019 (2019q1) up to and including the last quarter of 2021 (2021q4). This information comes from the VAT declarations administered at the Federal Finance Office. Third, for the universe of Flemish enterprises, we obtain information on employment in terms of both the number of workers (headcount) and full-time equivalents (FTEs), and the main economic activity at the NACE 5-digit level from the Social Security Office, reported quarterly between 2005q1 and 2021q4. We use this dataset to identify firm exit at the quarterly level, defined as not submitting compulsory social security statements in subsequent quarters up until the end of our dataset. Finally, we extract information on fixed assets, sales, value added, age, and debt-to-asset ratios for all enterprises in Flanders that submit annual accounts for the period 2005–2021 from Bureau Van Dijk.[3] Across these datasets, all enterprises are identified by a unique VAT number, allowing for unambiguous merging.

We retain enterprises across all market activities, spanning NACE (Rev. 2, 2008) 2-digit codes 01–82, thus including primary, secondary and tertiary sectors. We exclude NACE sector 78 (employment activities), which contains mostly temporary employment agencies: enterprises in this sector record large numbers of workers and FTEs, but those are not part of the production of these enterprises themselves, as they are rented out to other firms. We group some NACE 2-digit sectors to contain at least 250 observations, needed to estimate sectoral production functions and structural TFP.[4] See Appendix A for a list and description of these sectors. For the main analysis studying labor productivity, and to allow for comparable analysis throughout the different sections, we restrict the data to enterprises that report strictly positive value added, employment and capital. If one of these variables is missing in period t, we interpolate its value using a simple average of $t-1$ and $t+1$.[5] We do not impute gaps of more than one period. The event study requires a balanced sample, and firms with gaps of more than one period are also dropped from the aggregate productivity decomposition exercise to avoid spurious exit.

2.2. Enterprise-level support measures

As the government imposed stringent lockdowns and sector closures to curb the spread of the virus, flanking measures were issued to support enterprises that were forced to close or saw a large reduction in their sales. The goal of these emergency measures was to keep the economy afloat by allowing enterprises to keep making essential payments, to retain productive capacity, and to avoid firm failures, layoffs, and liquidity issues as a direct result of the sanitary policies that had been implemented. At the macro level, these support measures were intended to attenuate the resulting economic crisis and to accelerate economic recovery afterwards (Zegel et al., 2021).

Tandem measures were issued at the sector (NACE) level. For example, if a lockdown was imposed on all non-essential stores, enterprises that were active in these sectors would become eligible for the flanking support measures. Similarly, if social distancing implied that all contact professions (hairdressers, chiropractors etc.) would have to close, enterprises in these sectors would be eligible for compensation. These sector-specific measures with clearly stipulated firm-level requirements are separate from more general concurrent government intervention measures, such as furlough schemes, moratoria on bankruptcies, and financial instruments. We will exploit this variation in eligibility and firm outcomes in our identification strategy to obtain causal estimates of the impact of these support measures on enterprise-level outcomes. We provide a detailed discussion of the policy intervention logic and how it was perceived by enterprises in Section 6. We also provide a detailed description of the various policies, and a timeline of the lockdown policies and tandem support measures for enterprises in Appendix B.

The scale and speed of this program is truly impressive: enterprises could apply online through a dedicated website, and the application process only required some basic information on the enterprise (VAT number and legal name, the location of the main seat, a bank account number, and eligible sector of activity). The median payout rate was only two days after application. Between March 12 and December 31 2020, a total of 1.7 billion euros had been allocated through this program. It is important to note that these support mechanisms did not count as revenues in enterprises' accounts, which could otherwise lead to a mechanical positive correlation in support policies and firm productivity in the analysis below.

[2] We use 'enterprise' and 'firm' as synonyms throughout. In fact, the vast majority of support measures applies to enterprises in various services sectors, such as retail, wholesale, restaurants, accommodation etc., rather than to classic manufacturing firms.

[3] Only enterprises above certain size thresholds are required to submit annual accounts. Conditional on submission, micro and small enterprises can submit abbreviated annual accounts excluding sales and inputs expenditures, while large enterprises have to submit full accounts. See the size criteria here. The debt-to-asset ratio is calculated as the total debt (both short-term and long-term debt) divided by total assets.

[4] When estimating sector-level production functions to back out TFP, the NACE 2-digit code of a firm is treated as fixed over time.

[5] We impute at least one value for 3.6% of firms in the final dataset.

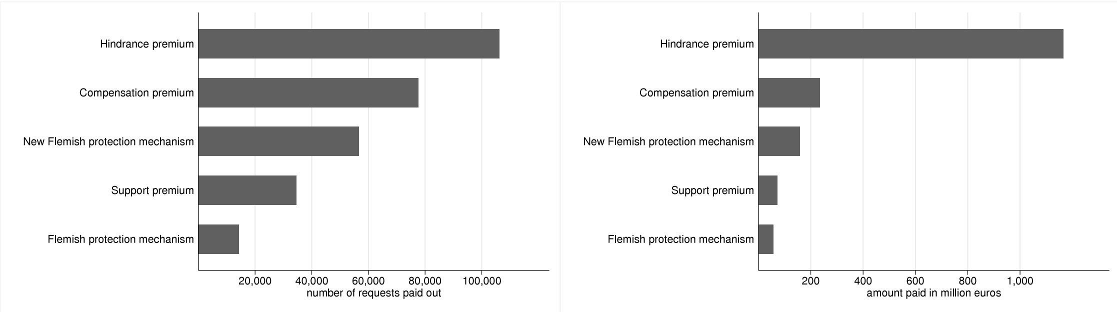

Fig. 1. VLAIO support, by mechanism.

Table 1
VLAIO support mechanisms.

Support measure	Description	Coverage period	First payout
1. Hindrance premium	Requirement: mandatory closure of physical site. Support: €160/day.	Mar 12–Jun 30	Apr 2, 2020
2. Compensation premium	Requirement: drop in turnover ≥60% relative to reference period in 2019. Support: €3,000. Half for self-employed in secondary occupation. Not cumulative with hindrance premium.	Mar 14–Apr 30	May 7, 2020
3. Support premium	Requirement: drop in turnover ≥60% relative to reference period in 2019. Support: €2,000. Half for self-employed in secondary occupation.	May 01–May 31	Jul 16, 2020
4. Flemish protection mechanism	Requirement: drop in turnover ≥60% relative to reference period in 2019. Support: 7.5% of turnover; with max €15,000. Half for self-employed in secondary occupation.	Aug 01–Sep 30	Sep 30, 2020
5. New Flemish protection mechanism	Requirement: drop in turnover ≥60% relative to reference period in 2019. Support: 10% of turnover; with min €1,000; max: €60,000 (based on FTE thresholds). Half for self-employed in secondary occupation.	Oct 01–Nov 15	Nov 17, 2020

To support enterprises as quickly as possible, the government initially opted for an existing support mechanism. In particular, the Hindrance premium was an existing tool to support shops and businesses that are forced to close due to e.g. extended infrastructure works in the street of their shop. This channel was used to provide the first wave of support over the second quarter of 2020. As restrictive policies changed throughout the year, the support mechanisms also evolved. Table 1 describes the five support measures that have been paid throughout 2020, the requirements and support amount, the coverage period, and the date the first payments were made. The measures can be broadly categorized along two dimensions: (i) support for mandatory closure (premium 1) versus experiencing a drop of at least 60% in turnover relative to the same period in 2019 (premia 2–5); and (ii) flat fee (premia 1–3) versus ad valorem support (premia 4–5).[6] All mechanisms were paid out in one shot, except the Hindrance premium, which was paid out in up to four parts over the second quarter of 2020.

Fig. 1 shows the number of enterprises that have obtained support and the total amounts paid out, by support mechanism. The first measure, the Hindrance premium, supported over 100,000 entities, for a total of almost 1.2 billion euro, accounting for almost 70% of the total support amount in 2020. This suggests that a large part of the expected impact of the overall program might in fact be contributed to the Hindrance premium. To evaluate this, we estimate the impact of the overall program on enterprise outcomes within enterprises over time, as well as the potentially different effects of the different mechanisms in Section 3.

There is also significant heterogeneity across sectors in terms of support. Fig. 2 shows the top 10 sectors in terms of the amount of VLAIO support received in 2020. Over 500 million euro was allocated to retail trade, followed by the food and beverage sector with almost 400 million euro. Other sectors include wholesale, specialized construction activities, accommodation, and travel agencies. Some of these sectors were also hit disproportionally hard by the stringent lockdown and social distancing policies, and often remained closed the longest. To account for this heterogeneity, we normalize productivity by sector and/or include sector fixed effects where necessary. We analyze within-firm evolution over time in the event study in Section 3, and weigh individual enterprises when aggregating and decomposing aggregate productivity growth in Section 4.

[6] We focus on the five mechanisms that supported firms with payouts in 2020. A sixth premium with the same characteristics as the fifth premium covered the period Nov 16–Dec 31, 2020. However, the application procedure and payments only started in 2021, and is thus left out of the analysis. We have also dropped payments of the five premia that occur only for the first time in 2021. This right tail contains at most 1% of first payments of the premia 1–4 and 9% of premium 5.

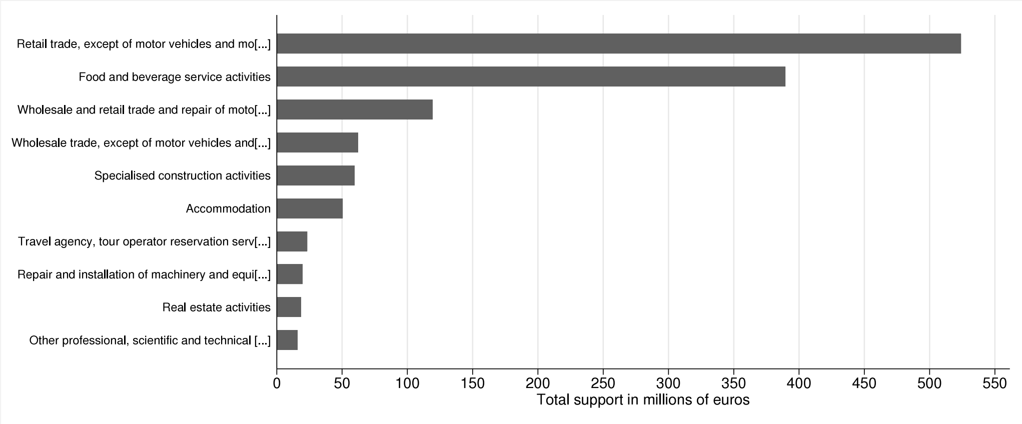

Fig. 2. Top 10 sectors, total value of support. Notes: Sectors are defined at the NACE (Rev. 2, 2008) 2-digit level.

2.3. Event study dataset

To estimate the causal impact of the Covid support measures on enterprise-level outcomes, we use the set of enterprises that applied for those support measures in 2020 and that also submit annual accounts. For these, we observe their quarterly performance for three full years, from 2019q1 to 2021q4. The VLAIO support mechanisms are sector-specific, depending on the sanitary measures in place at a given point in time. It is possible that some sectors, such as particular manufacturing sectors, were not eligible at all in 2020. To be eligible for support, enterprises had to be active in targeted sectors in 2019. We thus use a balanced panel of enterprise-quarter information: this allows to compare within-firm performance *ex ante* (2019) and *ex post* (2020–2021) support. The final dataset contains 78,972 firm-year observations for 26,324 firms over the period 2019–2021.

We calculate two measures of labor productivity, by combining quarterly information on FTE employment (Social Security) and sales (VAT declarations) with yearly information on value added (annual accounts). We use labor productivity as the baseline measure for the within-firm analysis. First, this allows us to carry out an analysis with quarterly productivity rates from sales and employment. Alternatively, estimating TFP as the residual from a production function estimation requires additional information on capital, which is only available at a yearly level from the annual accounts. Second, labor productivity is conceptually broader, as it also applies to firms outside of manufacturing, where outputs are not always measurable in terms of physical units, including services, accommodation etc. The latter are also the sectors that have been affected most by industry closures and eligible for the direct support schemes.

Our empirical analysis exploits information on firm outcomes across two groups. Enterprises in this dataset are either *treated* (they received support in 2020) or *never treated* (they applied for but did not receive support in 2020). Table 2 shows some summary statistics for raw variables in both groups for the year 2019, i.e. before the Covid shock. Interestingly, both the mean and median ($50th$ percentile) values of all variables are very similar, except for value added being on average larger for untreated enterprises. For example, the average number of FTEs for treated and untreated firms are 5.8 and 7.2 FTEs respectively, and their median is 2.3 versus 2.6. In terms of number of workers, the average is 6.9 and 8.3 respectively, while the median values are identical at 3 workers. Similar comparisons can be made for all moments of the other variables across both groups. Appendix C provides additional statistics, including summary statistics demeaned by NACE 2-digit sector, as well as information on the number of firms and the distribution of employment across firms by high-level industries.

These summary statistics provide a flavor of the distribution of supported versus unsupported enterprises. It is important to note however, that the identification strategy in the difference-in-difference setup in Section 3 is different from just comparing the two distributions across both groups. First, our outcome variable of interest is the *growth rate* of productivity, not its level.[7] We also provide kernel density plots on the full distribution of turnover, employment and productivity growth across both groups before the Covid shock in Appendix C. Second, the key identifying assumption is that the average outcome among the treated and comparison groups would have followed "parallel trends" in the absence of treatment. Pre-trends are tested statistically in Section 3, and include demeaning by both firm and sector-quarter fixed effects, as well as appropriate standard errors of these estimates. Third, the causal estimate of treatment is obtained by comparing the effect of support of the *treated* with a comparison group of *untreated*, the latter which includes both the not-yet-treated and the never treated.

[7] We run all specifications in levels with firm fixed effects, which is identical to calculating within-firm growth rates. Moreover, in Section 5 we provide additional results where we match treated firms to the pool of all non-treated firms (including those that never applied for support) that are closest to the treated firms in terms of the levels of FTE and capital stock. Our results are robust to this alternative control group setup.

Table 2
Summary statistics treated versus never treated (2019).

Sample	Variable	Mean	Std. dev.	Percentiles		
				10th	50th	90th
Treated (N = 23,049)	Employees (FTE)	5.8	30.2	0.6	2.3	11.5
	Employees (headcount)	6.9	38.8	1.3	3	13.5
	Value added	465,793	2,456,059	45,578	183,334	891,127
	Turnover	2,292,974	13,418,564	204,861	680,592	3,803,435
	Value added/FTE	126,067	594,293	42,609	74,621	177,064
	Turnover/FTE	706,401	3,254,355	178,006	292,323	1,098,652
Never treated (N = 3,275)	Employees (FTE)	7.2	25.1	0.7	2.6	14.2
	Employees (headcount)	8.3	28.1	1	3	13.5
	Value added	768,410	3,891,372	63,191	239,685	1,317,445
	Turnover	2,624,011	10,034,862	194,352	704,650	4,593,542
	Value added/FTE	147,804	446,478	50,097	87,019	222,249
	Turnover/FTE	614,204	3,669,736	114,005	263,016	960,200

Notes: This table reports the distributions of yearly variables of treated and never treated enterprises in 2019. Employment is expressed as the number of full-time equivalents (FTE) or number of employees (headcount) at the enterprise, averaged over all quarters in 2019; value added and turnover are the sum in euros over all quarters in 2019.

Table 3
Summary statistics productivity growth, pooled (2005–2021).

Variable	Mean	Std. dev.	Percentiles		
			10th	50th	90th
Employees (FTE)	12.1	83	0.6	2.8	20.0
Value added	1,306,534	15,967,020	48,061	227,119	1,725,210
Value added/FTE	152,170	1,799,713	41,583	78,233	211,182
Tangible fixed assets	1,204,518	20,698,849	9,649	132,862	1,202,357

Notes: Employment is expressed as the number of full-time equivalents (FTE); value added and tangible fixed assets are in current euros. All variables are yearly values, pooled over 2005–2020.

2.4. *Aggregate productivity growth dataset*

We construct a second dataset to evaluate the impact of the Covid support measures on aggregate productivity growth, reallocation and entry/exit. We use the universe of enterprises with annual accounts in Flanders from 2005 to 2021. This dataset differs from the event study dataset along two dimensions. First, to trace aggregate growth of the Flemish economy across the business cycle, this dataset consists of a long unbalanced panel of enterprises. Second, to measure aggregate growth of the economy, the dataset contains not only enterprises that applied for Covid-19 support measures, but also all other enterprises that did not apply for support. This thus also includes firms in sectors that did not face compulsory lockdowns in 2020. This setup allows us to decompose aggregate productivity growth into the contribution of several components: the average within-firm productivity growth, the reallocation of market shares across firm types, and the contribution of continuing, entering and exiting firms. The resulting unbalanced panel consists of 1,201,105 firm-year observations from 148,967 unique enterprises from 2005 to 2021. Table 3 provides a summary of the distributions of the main variables used for analysis, pooled over all years. On average, an enterprise in this dataset employs 12.1 FTE's, generates 1.3 million euro of value added a year, and has 1.2 million euro in capital stock. The average labor productivity is 152,170 euro value added per FTE. We use value added per FTE as labor productivity measure in Section 4, and structural TFP as a robustness in Section 5 and Appendix D, which also uses tangible fixed assets when estimating sector-level production functions.

3. The impact of covid support measures on firm performance

3.1. *Identification strategy*

We want to estimate the causal impact of firm-level support measures on firm performance. To do so, we exploit data on the population of enterprises for the years 2019–2021 that applied for support in 2020. We estimate a difference-in-differences setup. In particular, we compare enterprise outcomes before and after treatment (first difference) with enterprises that applied for but did not obtain support (second difference). We argue that the latter are a plausible control group: these firms were rejected because they provided insufficient information in the application, did not have an establishment in Flanders (but e.g. in Brussels or Wallonia), were not in a closed sector at that time for premium 1, or from premium 2 onwards, experienced a sales drop that was perhaps close to, but less than the required 60% in the reference period in 2019. In fact, potential non-random selection into treatment, e.g. enterprises that were rejected because they could remain open, or faced smaller drops in turnover than those in the treated group, would attenuate the difference in the averages across treated/untreated groups, thus if anything, biasing *downwards* our estimates of the true impact of the support measures on enterprise outcomes.

To plausibly estimate causal effects in this setting, three key assumptions need to hold: (i) the parallel trends assumption, (ii) no anticipation effects, and (iii) the stable unit treatment value (SUTVA) assumption. The first implies that, absent any treatment, on average the outcome of interest, productivity growth, of the groups of treated and non-treated enterprises would have evolved in parallel, conditional on both observable and unobservable characteristics. This assumption does allow for the *levels* of untreated potential outcomes to differ across groups. We test for pre-trends in the quarterly analysis to validate this assumption empirically. Second, the assumption on no anticipation effects implies that, for both treated and untreated, firm outcomes are not affected in periods before treatment. Since the pandemic did not hit Flanders until March 2020, rescue policies were issued in a matter of days, and the structure of these measures changed over time without announcements, the non-anticipation assumption is plausibly justified. We also provide a placebo test in which firms are counterfactually treated in the last quarter of 2019 and the first quarter of 2020 in Section 5. Finally, the SUTVA assumption states that one, and only one, potential outcome is observed for each unit in the population. In practice, this implies that potential outcomes for each unit are unrelated to the treatment status of other units. It is possible that there are partial and general equilibrium effects (e.g. equilibrium price responses and input–output linkages) that might induce such cross-unit spillovers. Unfortunately we do not have sufficient data to quantify such effects in our setup. Finally, SUTVA also implies that it does not matter if there is a difference in the size (number of observations) of the treated or untreated group.

Estimation proceeds as follows. We first estimate a canonical difference-in-differences model of two periods (2019 versus 2020–2021) and two groups (treated versus untreated). We then exploit the granularity of the data to estimate a quarterly event study. This allows to empirically validate the parallel trends assumption and the potential persistence effects of the support policies. Next, we estimate the two-period model for individual support mechanisms, to evaluate potential heterogeneity in the impact of different policies. Finally, we estimate the impact of treatment on the probability of firm exit.

In the baseline setting, we estimate the average treatment effect on the treated (ATT) from a zero–one treatment. We think this is reasonable. First, premia 1–3 are constant or lump sum treatments, i.e. without variation in treatment 'doses'. Second, if continuous treatment generates a non-linear response in the outcome variable, additional assumptions are to be invoked, and rather than the ATT, the estimated parameters capture the average causal response on the treatment group (ACRT). See Callaway et al. (2021) for a discussion on continuous treatment and its complexities of interpreting estimated parameters under treatment heterogeneity. Third, we cluster robust standard errors at the firm level, to account for potential autocorrelation between *ex ante* and *ex post* periods within the same unit.

We also provide several robustness results in Section 5, including a placebo test, additional controls for federal support schemes that might affect both treated and untreated firms, alternative control groups based on nearest neighbor matching, and the alternative estimator of Sun and Abraham (2021) to control for heterogeneous treatment effects in a pooled estimation setup. We also split labor productivity growth into its components, sales or value added, and FTE growth.

3.2. Pre and post effects of support

We first estimate the overall effect of the Covid support mechanisms in 2020 on firms' productivity in 2020 and 2021. Under the stated identifying assumptions, and for two periods and two groups, the ATT can be consistently estimated using a Two-Way Fixed Effects (TWFE) regression of the following form (Roth et al., 2022):

$$Y_{it} = \beta D_{it} + \alpha_i + \lambda_{jt} + \varepsilon_{it} \tag{1}$$

where we measure labor productivity Y_{it} either as log sales per FTE or log value added per FTE. There are two periods: $t = 0$ for the year 2019 ("*pre* treatment"), and $t = 1$ for the years 2020–2021 ("*post* treatment"). $D_{it} = 1$ if enterprise i received support in period t, and 0 otherwise. Firm fixed effects α_i control for firm-level unobservables that are constant *ex ante* and *ex post* treatment, and allow to evaluate the within-firm effect of treatment on productivity outcomes. We also include industry-year fixed effects λ_{jt}, where j indexes the industry of enterprise i at the 2-digit NACE level. These fixed effects control for common aggregate trends, such as the massive Covid shock in 2020, potential recovery in 2021, as well as heterogeneity in industry growth rates, due to e.g. variation in the stringency of imposed sanitary polices and recovery rates afterwards. In Appendix E, we also provide estimates using only firm and year fixed effects.

Table 4 shows the results of estimating Eq. (1). Compared to untreated firms within the same sector, enterprises that received Covid support experienced a positive and significant impact on productivity: the ATT is 4% or 4.7%, depending on the measure of labor productivity we use. This suggests that enterprises that received support have been able to increase their labor productivity more *ex post* than the control group of enterprises that did not receive support within the same sector. It is possible that all firms experienced a strong negative shock to labor productivity. To the extent that enterprises receiving support were also hit more by a negative shock than untreated firms, this would suggest that the overall policy helped treated enterprises to catch up again with others that were *ex ante* similar in terms of productivity growth. We return to this hypothesis in the aggregate productivity growth results in Section 4.

3.3. Quarterly event study

Next, we look at the impact of the policy in more detail, using quarterly data on treatment and firm outcomes. This has at least two advantages for identification. First, enterprises could have received support in the second, third or fourth quarter of 2020. The quarterly analysis allows for a staggered treatment model, with some enterprises receiving support for the first time in the second

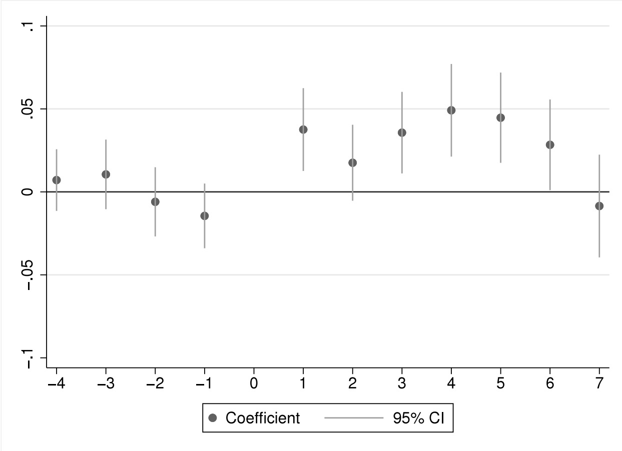

Fig. 3. Impact of support measures on productivity, quarterly.
Notes: Both firm fixed effects and industry-quarter fixed effects are included. Heteroscedastic robust standard errors are clustered at the firm level.

Table 4
Impact of support measures on productivity, pre/post.

	ln (sales/FTE)	ln (value added/FTE)
Treatment D_{it}	0.040**	0.047**
	(0.014)	(0.015)
Industry-year fixed effects	Yes	Yes
Firm fixed effects	Yes	Yes
Adj. R^2	0.81	0.59
N	78,972	78,972

Notes: Heteroscedastic robust standard errors are clustered at the firm level. Significance: * <5%, ** <1%, *** <0.1%.

quarter, others only in the third or fourth quarter, and others receiving no support at all in 2020. Second, this setup allows to estimate the persistence of a policy shock on firm outcomes. Firm-level support might affect firm outcomes in the same period, or only kick in later, and/or it might affect outcomes over more than one period only.

Following the literature (Roth et al., 2022), we consider enterprises to be treated from the first quarter they receive support. We estimate the following TWFE model:

$$Y_{it} = \sum_{k=-4}^{-1} \beta_k D_{ik} + \sum_{k=1}^{7} \beta_k D_{ik} + \alpha_i + \lambda_{jt} + \epsilon_{it} \tag{2}$$

We measure Y_{it} as log sales per FTE, as information on value added per FTE is only available at a yearly level. The treatment dummies D_{ik} indicate whether the enterprise got the first support in quarter k relative to quarter t, where $k = 1$ indicates the first quarter of support. The treatment dummies are split into a pre-treatment period ($k = -4, \dots, -1$) and a post-treatment period ($k = 1, \dots, 7$). Coefficients are normalized to zero in $k = 0$, the quarter before an enterprise received support.[8] This setting allows for heterogeneous treatment effects within firms *over time*. Heterogeneous treatment effects *across firms* are further explored in the next section and in Section 5. We control for firm fixed effects α_i, and industry-quarter effects λ_{jt}.

Fig. 3 plots the coefficients from estimating Eq. (2) for all quarters k, together with 95% confidence intervals. Some notes. First, point estimates for the four pre-treatment quarters are not statistically significant different from zero, supporting the parallel trends assumption in the observed time frame. This also suggests there are no anticipation effects or SUTVA violations from pre-treatment outcomes in this staggered setting. Second, the estimated treatment effect is around 4% in the first quarter post treatment, and – with the exception of the second quarter – remains positive and significant up to six periods post treatment. The 7th quarter turns insignificant. This suggests that the policy generated significant effects in productivity growth after intervention, with a reversion to the mean towards the end of the period. In other words: on average, the support policy provided a positive and significant productivity boost up to six quarters post intervention. Yet the effect is plausibly temporary, as the productivity growth of supported enterprises is no longer distinguishable from that of non-supported enterprises at the end of the panel period.

[8] Hence, $k = 0$ is 2020q2, 2020q3 or 2020q4, and $k = 7$ is 2021q4 for firms that received treatment in 2020q2.

Table 5
Difference-in-differences by support mechanism, pre/post.

	ln (sales/FTE)	ln (value added/FTE)
Premium 1	0.043***	0.071***
	(0.015)	(0.017)
Premium 2 or 3	0.028	0.017
	(0.015)	(0.017)
Premium 4 or 5	0.013	0.004
	(0.025)	(0.030)
Industry-year fixed effects	Yes	Yes
Firm fixed effects	Yes	Yes
Adj. R^2	0.87	0.73
N	78,972	78,972

Notes: Heteroscedastic robust standard errors are clustered at the firm level. Significance: * <5%, ** <1%, *** <0.1%.

3.4. Diff-in-diff by premium

We next estimate the impact of support measures on firm outcomes by type of measure. There are several reasons why the different support measures may have a differential effect on firm performance. First, there is sizable variation in the amounts allocated through each support type, and premium 1 was by far the largest support scheme in terms of both number of applications and allocated funding. This might suggest that, on average, premium 1 contributed most to the total effect of the intervention policy. Second, mechanisms varied in their particular requirements: forced closure (premium 1) versus a significant drop in turnover (premia 2–5). Third, mechanisms also varied in terms of the level of support allocated to firms: flat fees (premia 1–3) versus *ad valorem* fees (premia 4–5). Variation in these support measures might provide some information on underlying mechanisms on outcomes. To elaborate on these distinctions, the support mechanisms are divided into three groups; the hindrance premium (premium 1), the compensation and support premium (premia 2 and 3), and the Flemish protection mechanism and new Flemish protection mechanism (premia 4 and 5). If a firm received more than one support mechanism, each dummy reflects the first support measure that a particular firm has received.

Table 5 shows the results. Both sales and value added measures of labor productivity are used as outcome variables. We report coefficients as the total effect of treatment, i.e. the sum of a dummy of treatment plus the effect of the individual mechanism.[9] The first premium constitutes the bulk of total value and number of enterprises supported, so it might have a large effect on the overall ATT. The premium was targeted at firms that had to close down and consisted of a lump sum of 160 euro per day. Indeed, the point estimate for the average treatment effect of premium 1 ranges between 4.3% and 7.1% depending on the productivity measure. The second and third premia are also characterized by a lump sum, of 3000 and 2000 euro respectively, conditional on a sales drop of at least 60%. However, we do not find a significant difference from the evolution in the control group for these premia. The point estimate of the total effect is still positive at 2.8% or 1.7%, but not significantly different from zero. For premia 4 and 5, the value of the support is calculated as a percentage of turnover in the reference period in 2019. The average treatment effect for firms that got ad valorem fees is smaller than that of the other premia and insignificant. These results suggest that the average effect per enterprise of the support policies in 2020 on outcomes in 2020 and 2021 can be largely contributed to the first premium. Intuitively, this was also the premium that supported the largest number of firms, with the largest monetary support, and at the beginning of the crisis.

3.5. Propensity to exit

We conclude this section by studying the impact of the VLAIO support measures on firm exit. One of the rationales for the support program was to avoid firm exit as a direct consequence of the sanitary restrictions imposed by the government. During most of 2020 and for parts of 2021, there was a moratorium on bankruptcies in Belgium, i.e. bankruptcy procedures were temporarily suspended by the ruling courts. In fact, firm exit in 2020 and 2021 was at the lowest rate since the financial crisis in 2008. Firms could still be liquidated voluntarily though, e.g. when experiencing liquidity or solvency issues. Hence, firm exit was still positive, albeit much lower than in normal times. See Appendix B for a more detailed discussion on the bankruptcy moratoria.

We therefore analyze how the Covid support measures affected firm exit. The control group now also includes all enterprises that did not request support, to enlarge the set of potentially exiting firms.[10] We also provide additional robustness results for the smaller control group of firms that applied for support in Section 5. Table 6 shows the results of a logit regression of firm exit on the treatment status of firms, controlling for standard variables that are known to predict exit: bigger, older, more productive enterprises with lower debt-to-asset ratios are generally known to have lower exit rates. Conditional on these controls, the estimated

[9] In particular, we regress $Y_{it} = \beta_1 D_{it} + \beta_2 P1_{it} + \beta_3 P2_{it} + \beta_4 P3_{it} + \alpha_i + \lambda_{jt} + \varepsilon_{it}$, where $P1$ refers to premium 1, $P2$ to premium 2 or 3, and $P3$ to premium 4 or 5. The average effect of $P1$ on Y_{it}, compared to no support, is then $\beta_1 + \beta_2$, etc.

[10] Recall that we could not include these firms in the productivity analysis above, as we do not observe quarterly sales for enterprises that did not apply to the Covid support schemes. But we do observe exits for all firms from the quarterly social security data, which we use here.

Table 6
Probability of exit, quarterly.

	Pr (exit)	Pr (exit)	Pr (exit)
Treatment D_{it}	−0.57***	−0.57***	−0.57***
	(0.12)	(0.12)	(0.12)
ln (value added/FTE)	−0.25***	−0.25***	−0.25***
	(0.04)	(0.03)	(0.03)
ln (FTE)	−0.96***	−0.96***	−0.96***
	(0.05)	(0.05)	(0.05)
debt/asset ratio 2019		0.06**	0.05**
		(0.03)	(0.03)
ln (age)			−0.02
			(0.03)
Unconditional exit probability	1.1%		
Quarter fixed effects	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes
Pseudo R^2	0.15	0.15	0.15
N	217,508	217,508	217,508

Notes: Exit is a dummy variable which indicates whether a enterprise will exit in the next quarter. Heteroscedastic robust standard errors are clustered at the industry level. Significance: * <5%, ** <1%, *** <0.1%.

Table 7
Decomposition of exit probabilities.

Scenario	Pr (exit)
Unconditional exit probability	1.1%
Average exit probability: Treated	1.0%
Average exit probability: Untreated	1.1%
Counterfactuals	
1. If no firms had received support	1.2%
2. If firms that did get support had not received support	1.7%
3. If all firms had received support	0.7%
4. If firms that did not get support had received support	0.6%

Notes: The decomposition shows the average exit probabilities implied by the logit coefficients from Table 6.

impact of support on exit is substantial: the average marginal effect of receiving support is a decline in the probability of exit of 0.5 percentage points, or 45% compared to the unconditional probability of exit of 1.1%.[11]

To interpret this result, Table 7 shows the decomposition of predicted exit probabilities. In the logit model, the predicted probability of exit can be calculated for each observation based on its covariates. The average of the predicted exit probabilities in the group of treated firms is 1%, while the average for the untreated is 1.1%. One can also calculate counterfactuals from the logit coefficients, where the values for the covariates stay unchanged and the values for the treatment dummy are altered. When no firms had received support, the average exit probability would have been 1.2%, which means the support program has decreased the total exit rate by 0.1 percentage points. The logit estimates also imply that the average exit probability for the group of supported enterprises would have risen from 1% to 1.7% in the case of no support, or an increase of 70%. If all firms had received support, the average exit probability would have been 0.7%. The difference between the two counterfactuals of no support and support to all firms boils down to the average marginal effect of support. Finally, if the firms without support had been supported, the average exit probability of these firms would have been 0.6%. These results show that supported enterprises have a significant lower probability to exit, relative to similar but untreated firms. However, whether this policy was efficient from an aggregate perspective, or whether it affected creative destruction, depends on the relative contribution of entry and exit on aggregate productivity growth and on how incumbent firms have been affected. We turn to this in the next section.

4. Aggregate productivity growth, covid support and reallocation

4.1. Aggregate productivity growth and its main components

We first document aggregate productivity growth for Flanders over the period 2006 to 2021. Fig. 4 shows the year-over-year growth rates of labor productivity, expressed as the weighted average of firm-level value added per FTE, with weights given by firms'

[11] The marginal effect of support for a firm is the derivative of the probability of exit with respect to receiving support based on the firm's covariates. When y is the exit variable (1 if a firm exits, 0 if not), X is the vector of covariates and β that of estimated logit coefficients, the marginal effect of X_1 on exit can be described as $\frac{d\Pr(y=1)}{dX_1} = \frac{\beta_1 exp\{-X'\beta\}}{(1+exp\{-X'\beta\})^2}$. The average marginal effect follows as the average over all firms.

FTE shares across all firms in the economy. The figure also shows the growth rates of the labor productivity components, value added and FTE, separately. Aggregate labor productivity growth (solid line) in 2020 and 2021 is positive, with a year-over-year growth rate of 5.9% and 2.1% respectively. Both aggregate value added (dashed line) and the number of FTE (dotted line) drop drastically in 2020. However, the drop in FTE employment (−7.5%) was much larger than the drop in value added (−1.7%), generating the positive labor productivity growth. In 2021, employment recovers, with a growth rate of FTE of 1.4%, and value added at 0.05%.

Some notes. First, our measure is constructed as a weighted average growth rate using firm-level data, following Melitz and Polanec (2015). This allows us to perform an exact decomposition into the various productivity components, including a further distinction between the contributions of treated and untreated firms. Our micro aggregations and official aggregate statistics are not necessarily the same.[12] Nevertheless, our goal is not to match aggregate statistics *per se*, but to evaluate the signs and relative contributions of individual components to aggregate productivity growth. Here, some generic and consistent patterns arise across methods and datasets in 'normal' times: (i) most productivity growth comes from within-firm growth, (ii) a reallocation of market shares towards more productive firms is productivity improving in the aggregate, and (iii) the net contribution of entry and exit of firms is positive.

Second, from a theoretical perspective, the relationship between GDP growth and productivity growth during recessions is *a priori* ambiguous. Some models predict that negative GDP growth hampers productivity levels and growth due to human capital destruction or misallocation (e.g. Grossman and Helpman (1991)), while models of Schumpeterian creative destruction predict cleansing effects of recessions on productivity (Caballero and Hammour, 1994, 1996). Hence, the extent to which recessions impact productivity is largely an empirical question. We do see variation in these patterns across recessions in our data. For example, during the financial crisis and the Great Recession, aggregate labor productivity growth was −0.4% in 2008 and 0.6% in 2009, contributing in a sluggish recovery, consistent with the 'lost decade' of EU economic growth. Conversely, we see positive growth rates of 5.9% and 2.1% in 2020 and 2021.

Third, we do not take a stance on whether these growth rates are structural, or relate to long-run equilibrium outcomes. We discuss several potential mechanisms and whether such productivity growth could be temporary or permanent in Section 6.

4.2. Decomposing aggregate productivity growth

Next, we turn to the contribution of individual firms to aggregate productivity growth. Aggregate log productivity at time t, Φ_t, is given by:

$$\Phi_t = \sum_{i \in N_t} s_{it} \varphi_{it} \tag{3}$$

That is, aggregate log productivity is a weighted average of firm-level log productivity φ_{it}, with weights given by market shares, s_{it}. Productivity is measured as value added per FTE, and market shares are measured in terms of FTE. We provide additional results for structural TFP using a control-function approach in Section 5.[13] Aggregate productivity can be decomposed into an unweighted average of firm productivity and a covariance term (Olley and Pakes, 1996):

$$\begin{aligned} \Phi_t &= \bar{\varphi}_t + \sum_{i \in N_t} \left(s_{it} - \bar{s}_t\right)\left(\varphi_{it} - \bar{\varphi}_t\right) \\ &= \bar{\varphi}_t + Cov(s_{it}, \varphi_{it}) \end{aligned}$$

where $\bar{s}_t = \frac{1}{N_t}\sum_{i \in N_t} s_{it}$ and $\bar{\varphi}_t = \frac{1}{N_t}\sum_{i \in N_t} \varphi_{it}$ are the unweighted averages of market shares and productivity levels respectively. A positive covariance term implies that more productive firms have higher market shares, implying higher levels of allocative efficiency. Aggregate productivity can increase due to (i) a shift in the firm-level productivity measure $\bar{\varphi}_t$, and/or (ii) a reallocation of market shares to more productive firms.

Building on this, Melitz and Polanec (2015) provide a decomposition of aggregate log productivity growth, $\Delta\Phi_t$:

$$\triangle \Phi_t = \triangle \bar{\varphi}_t + \triangle \sum_{i \in N_t} \left(s_{it} - \bar{s}_t\right)\left(\varphi_{it} - \bar{\varphi}_t\right)$$

[12] Micro aggregations and aggregate statistics can differ due to differences in methodology, data sources, timing of collection, *ex post* updating of official statistics etc. Moreover, even with the same micro data, different productivity measures can generate differences in growth rates. For example, labor productivity measures are consistently larger than TFP measures for the US (Pancost and Yeh, 2022), and estimates from value added production functions are also larger than those from gross output production functions (Brandt et al., 2012). While we do not yet have official statistics for Flanders, Eurostat reports a preliminary growth rate of real labor productivity per hour worked of 3.2% for Belgium in 2020. The Belgian National Council for Productivity compares productivity growth across several EU countries (Austria, Belgium, Finland, France, Germany, Italy and the Netherlands), and finds the strongest increase in Belgium at 3.6% (National Council for Productivity, 2021). Other highly developed countries, such as the US, also experienced positive productivity growth in 2020 (Van Ark et al., 2021; Gordon and Sayed, 2022). For 2021, Eurostat reports a real labor productivity growth rate for Belgium of −1.3%. Additionally, official statistics for Belgium can plausibly be considered underestimations of labor productivity growth in Flanders. While we cannot compare productivity growth rates for Flanders against those for Belgium, we do have official statistics on GDP growth at the regional levels. The National Bank of Belgium reports a smaller decline of nominal GDP for Flanders (−3.6%) compared to Belgium (−3.9%) for 2020, and a larger recovery in 2021 (9.9% versus 9.2%). Note that these statistics are still preliminary for both 2020 and 2021.

[13] The intuition for labor productivity growth easily carries over to TFP. Technically, TFP is estimated as the residual from estimating a sector-specific Cobb–Douglas production function $\ln$ (value added) − $\beta_l \ln$ (FTE) − $\beta_k \ln$ (tangible fixed assets). If capital remains relatively stable from one year to another, the labor productivity dynamics also drive TFP growth. However, the effect of FTE dropping faster than value added is only partially considered through β_l. This explains why labour productivity increases more than TFP, at least mechanically.

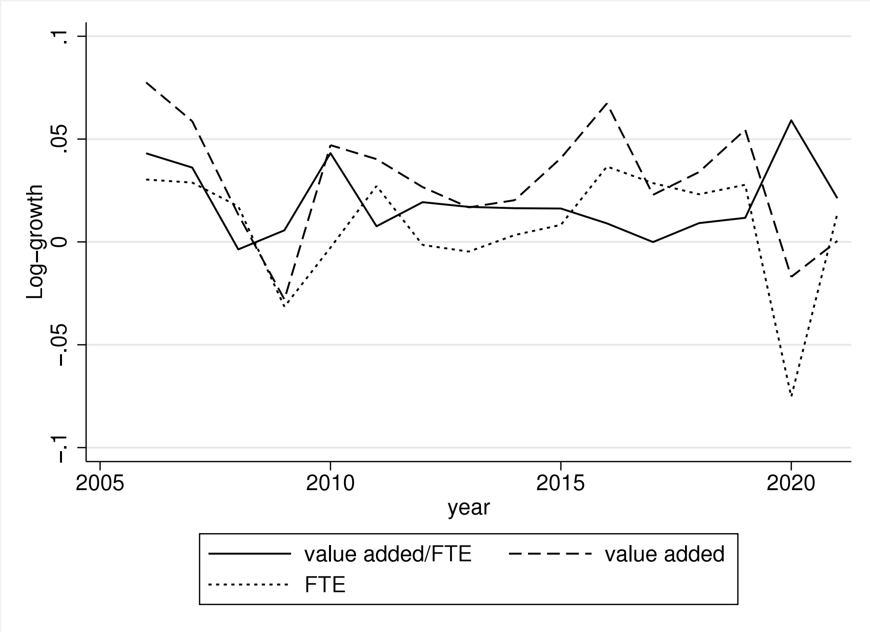

Fig. 4. Aggregate growth rates of labour productivity, value added and employment (2006–2021). Notes: Yearly growth rates are expressed in log-differences.

$$
\begin{aligned}
&= \triangle\, \bar{\varphi}_t + \triangle\, Cov(s_{it}, \varphi_{it}) \\
&= \underbrace{\triangle\, \bar{\varphi}_t^S + \left(Cov(s_2^S, \varphi_2^S) - Cov(s_1^S, \varphi_1^S)\right)}_{\text{survivors}} + \underbrace{s_2^E \left(\boldsymbol{\Phi}_2^E - \boldsymbol{\Phi}_2^S\right)}_{\text{entrants}} + \underbrace{s_1^X \left(\boldsymbol{\Phi}_1^S - \boldsymbol{\Phi}_1^X\right)}_{\text{exiters}}
\end{aligned}
$$

where S, E and X denote the partition of all firms into survivors, entrants and exiting firms respectively, and $t = 1, 2$ first and second periods. Aggregate productivity growth can be decomposed into four components. First, aggregate productivity increases in the within-firm unweighted average productivity growth of survivors, $\triangle\, \bar{\varphi}_t^S$. Second, it increases when the covariance of survivors, $Cov(s_2^S, \varphi_2^S) - Cov(s_1^S, \varphi_1^S)$, increases. This can happen in two ways: if more productive firms gain market shares, or if larger firms become more productive. Third, the share-weighted productivity contribution of entrants, $s_2^E \left(\boldsymbol{\Phi}_2^E - \boldsymbol{\Phi}_2^S\right)$, is positive if productivity of entrants is greater than that of survivors in period 2. Finally, the share weighted productivity component of exiting firms, $s_1^X \left(\boldsymbol{\Phi}_1^S - \boldsymbol{\Phi}_1^X\right)$, is positive if the productivity of survivors is greater than that of exiting firms in period 1.

Fig. 5 shows the results of this growth decomposition for the years 2006 to 2021. We report tables with detailed numbers underlying the decomposition graphs, as well as decompositions for manufacturing and services industries separately in Appendix E. Some notes. First, yearly productivity growth rates are the same as in Fig. 4. Aggregate productivity growth is positive and large (5.9%) in 2020 and positive but smaller (2.1%) in 2021. Second, the largest contribution in both 2020 and 2021 comes from within-firm productivity growth of survivors, a recurrent finding in the literature. (All following numbers are in terms of percentage points contribution to aggregate productivity growth:) The within-firm effect is particularly strong in 2020 and 2021, compared to other years at 8.5 and 4.3. Third, the covariance or reallocation term is negative in both 2020 and 2021 at −3.5 and −1. This implies that less productive firms gained market shares, or that smaller firms became more productive. Interestingly, this covariance term already turned negative in 2018: is this perhaps part of a longer trend in the Flemish economy? Fourth, in 2020, the contribution of entrants is slightly negative at −0.3, while the contribution of exiting firms is positive however, at 1.3. In 2021, the entry effect is −0.5, and the exit effect also turns negative at −0.7.

What is the total impact of the recession in 2020 on creative destruction? We can evaluate two margins of creative destruction: an extensive margin, which is the contribution of net entry and exit of firms, and an intensive margin, which is the reallocation of market shares towards more productive firms. On the extensive margin, the net entry effect is positive at +1, suggesting cleansing effects of a crisis from firm churn. On the intensive margin however, the reallocation effect is large and negative at −3.5. A negative reallocation term implies that it hampers aggregate productivity growth. In this respect, the Covid-19 crisis diverges from previous recessions, generally characterized by pro-cyclical within-firm productivity growth and a positive covariance term (Van den bosch and Vanormelingen, 2023), a pattern we also see during the 2008–2009 crisis. Taken together, these results point to insufficient creative destruction in 2020, attenuating the large boost of within-firm productivity growth. Creative destruction also turns out to be hampered in 2021: while the reallocation component is still negative but smaller at −1, the net entry component is now also negative at −1.3, due to a negative contribution of exiting firms, in fact for the first time over our time period. This suggests that there has been excessive firm exit during the Covid crisis, even with the battery of support measures that have been injected into the economy. However, the reallocation effect has been large and negative since 2018, contributing to insufficient creative destruction

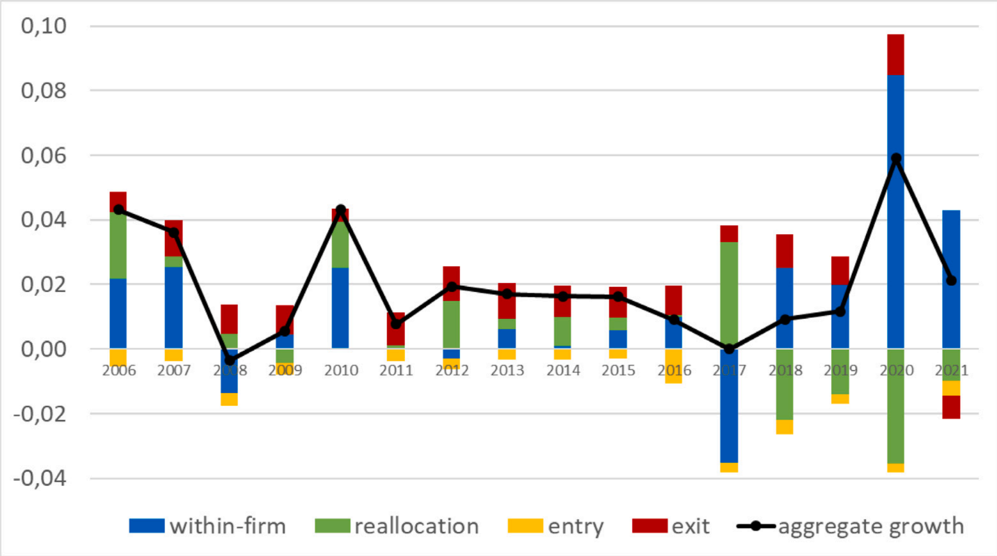

Fig. 5. Decomposition of aggregate labor productivity growth.

well before the Covid-19 crisis. While we do not know what would have been the counterfactual growth path if no support measures had been issued, we can further investigate the impact of support measures on treated firms compared to untreated firms, which we turn to now.

4.3. Decomposition across treated and untreated

What can we say about the impact of the support measures on aggregate productivity growth? To answer this question, we extend the decomposition above to quantify the contributions of both treated and untreated firms to aggregate productivity growth. It is important to note that the untreated group contains all other firms in the economy that are not treated, thus including those that applied for support but did not obtain it, as well as all other firms in the economy that did not apply for support, and were e.g. potentially in other sectors that did not face sanitary restrictions in 2020 at all.

This decomposition generates the same four components, now by subgroup, and an additional covariance term that measures the shift in market shares and productivity from treated to non-treated firms. This last component evaluates the impact of the Covid support mechanisms on allocative efficiency. We provide a derivation of this decomposition in Appendix F. Each firm i belongs to a subgroup $g = \{\text{treated}, \text{untreated}\}$. Aggregate productivity of subgroup g in levels is then denoted as

$$\Phi_t^g = \sum_{i \in g} \left(\frac{s_{it}}{s_t^g} \right) \varphi_{it}$$

where $s_t^g = \sum_{i \in g} s_{it}$ is the total market share of subgroup g, so that $\sum_g s_t^g = 1$. Let us focus on the components for surviving firms. Average within-firm productivity growth of surviving firms is then the weighted average of within-group growth of surviving firms, with weights given by the fraction of treated and non-treated firms:

$$\triangle\, \bar{\varphi}_t^S = \sum_{g=1}^{2} n^{S,g} \Delta \bar{\varphi}_t^{S,g}$$

where $n_t^{S,g}$ is the weight given to group g in t for surviving firms, calculated as the ratio between the number of surviving firms in group g and the total number of surviving firms in t, and $\Delta \bar{\varphi}_t^{S,g}$ is the unweighted average growth rate of surviving firms S in group g at time t.

The covariance or reallocation component now has two different elements: an intra-group change in covariance and an inter-group change:

$$\triangle\, cov_t^S = \underbrace{\sum_{g=1}^{2} n^{S,g} \left(\Delta Cov \left(s_t^{S,g}, \varphi_2^{S,g} \right) \right)}_{\text{intra-group reallocation}} + \underbrace{\left(\Delta Cov_{inter,t}^S \right)}_{\text{inter-group reallocation}}$$

The change in intra-group covariance is defined as before, but now aggregated by subgroups g with weights $n^{S,g}$. It measures the change in covariance between market shares and productivity within a group. A positive component implies an improvement of

Table 8
Decomposition of aggregate productivity growth, by treated/untreated.

Year	Agg. gr. survivors	*Treated*		*Untreated*		Between group reallocation
		Within firm	Covariance	Within firm	Covariance	
2020	0.050	0.041	−0.031	0.044	−0.016	0.011
2021	0.033	0.026	−0.011	0.017	0.006	−0.004

allocative efficiency, or improved creative destruction on the intensive margin for that subgroup. The new inter-group reallocation component measures the shift in the covariance between market shares and productivity across groups, from treated to untreated, and is given by

$$\Delta Cov^{S}_{inter,t} = \sum_{g=1}^{2} \Delta(s^{S,g}_{t} - n^{S,g})(\Phi^{S,g}_{t} - \Phi^{S}_{t})$$

A positive value for a subgroup g implies that firms in a group with higher aggregate productivity $\Phi^{S,g}_{t}$ see their market shares $s^{S,g}_{t}$ increase, and/or groups with larger market shares see an increase in their aggregate productivity. If these effects outweigh the offsetting effects from market shares in the other group, the total component is positive.

Table 8 shows the results for this extended decomposition for the years 2020–2021. We focus on the evolution of surviving firms. First, the aggregate growth rate of survivors in column one is equal to the sum of columns 2 and 3 in Table 17. For 2020, this is 5 p.p. $= 8.5 + (-3.5)$. Second, in 2020, within firm productivity growth for both groups is relatively similar at around 4 p.p. Given that the number of treated firms in the aggregate is much smaller than the non-treated (including all sectors that did not receive VLAIO support), this implies that the treated firms contribute more on average per firm to aggregate productivity growth. This is in line with our findings in Section 3, and suggests that the productivity growth was not just a catch-up effect, but treated firms in fact contributed disproportionally more to positive productivity growth. In 2021, within-firm productivity growth is even larger for the group of treated firms at 2.6 versus 1.7 p.p.

When we look at the covariance terms for both groups, we see that both are negative in 2020, but that of the treated (−3.1 p.p) is twice as large as that of the non-treated (−1.6 p.p.). Moreover, the covariance term remains negative in the treated group in 2021 at −1.1, while turning slightly positive for the untreated at 0.6 p.p. This suggests that, within both groups, creative destruction along the intensive margin is hindered during the Covid pandemic, but this effect is stronger for the treated group.

When we turn to the between-group reallocation effect in the last column, we see that the covariance term is positive in 2020 at 1.1 p.p., with a small reversion in 2021 at −0.4 p.p. Two factors are at play. On the one hand, this is caused by a reallocation of market shares from treated to untreated firms, which had a higher aggregate productivity at the start of the crisis. The market share in terms of FTE of untreated firms rises with more than 3 percentage points, from 79.7% in 2019 to 82.8% in 2020. The positive between-group reallocation term thus suggests a positive effect of creative destruction towards more productive, untreated firms at the level of the economy. On the other hand, the aggregate productivity of untreated firms – which had a larger market share at the start – increases more due to the difference in the covariance terms in both groups described above.

In conclusion, in the aggregate, we find a negative reallocation effect of market shares towards less productive firms. This might signal insufficient creative destruction at the level of the economy. When we disaggregate more, in both treated and untreated groups, this negative reallocation term exists. This suggests that insufficient creative destruction persists across both treated and non-treated groups. However, there is a positive reallocation effect from treated to untreated more productive firms, as untreated firms gain larger market shares at the expense of treated firms, and untreated firms exhibit a larger productivity growth in the aggregate. While treated firms show higher productivity growth rates within sectors, some of the aggregate effect might be driven by sectors that have not been strongly hit during Covid, and that have a large aggregate share. Some sectors in fact saw large increases in turnover in 2020, like Insurances (NACE 65 A) with 79%, Extraction of Oil and Gas (NACE 6 A) with 41%, Residential Nursing Care Activities (NACE 87 A) with 13%, or Manufacturing of Pharmaceuticals (NACE 21 A) with 9%. Several of these sectors had clear reasons to expand during the pandemic.

5. Robustness

In this section, we discuss additional robustness exercises to the main results in Sections 3 and 4.

5.1. Placebo test with fake treatment

To further evaluate the credibility of our event study results, we conduct a placebo study where first treatment is assumed to have arrived one period earlier. The support dummy that was handed out in 2020q2 is reassigned to 2020q1, for 2020q3 to 2020q2, and for 2020q4 to 2020q3. We thus give all treated firms a fake treatment of support, pretending to take place before actual treatment. The idea is that a fake treatment should have no impact on the real outcomes of a firm. If we do pick up significant effects of fake treatment, this might suggest that our main setup picks up unobserved effects that generate a differential outcome across treated and untreated firms. The results of the placebo study are shown in Fig. 6. One pre-period is lost due to the shifted treatments. Since we shift treatment one period, there is one post-period of placebo treatment. In summary, the coefficients for the pre- and post-periods are not significantly different from zero, suggesting that the estimated treatment effects reflect the impact of the support and not a potential structural discrepancy between treatment and control group.

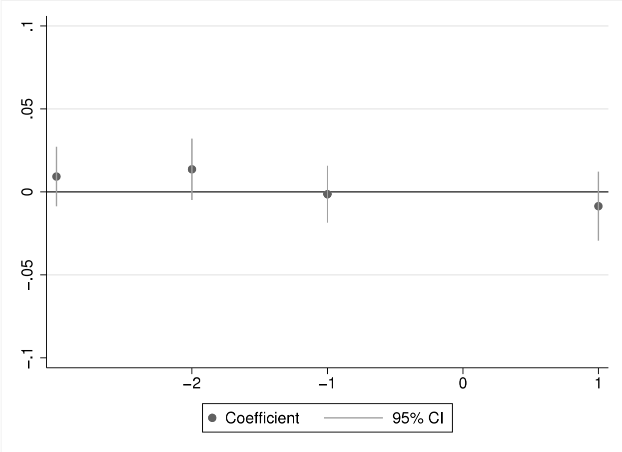

Fig. 6. Placebo test, quarterly diff-in-diff.
Notes: This figure shows the event study coefficients for the impact of support on labour productivity when treatment is brought forward one period as a placebo test. Both firm fixed effects and industry-quarter fixed effects are included. Heteroscedastic robust standard errors are clustered at the firm level.

5.2. Workers, FTEs and furlough schemes

In the Social Security data, we observe both FTE and the number of workers (head count) for every firm-quarter. We discuss two related points on employment. First, we use FTE as the reasonable measure to construct labor productivity: these are the workers actively involved in the production process, and FTE accounts for potential part-time workers at the firm, as it measures the number of hours worked in terms of FTEs. Second, the Social Security data allows to track the evolution of furlough schemes at the firm level. In particular, a worker that is active in the production process in one period is counted towards FTE. If this worker is put on a furlough scheme, it still counts as a worker at the firm, but is no longer counting towards the FTE number. The massive cushioning effect of the Belgian furlough schemes is clearly visible in the Social Security data: while aggregate unemployment only drops with 0.8% in 2020, the drop in aggregate FTE is 7.4%. The difference can be almost fully allocated to the use of these furlough schemes.[14] We discuss the Belgian furlough schemes in more detail in Appendix B, and provide additional difference-in-differences results, controlling for these federal schemes.

At the peak of the pandemic, in April 2020, around 690,000 employees were on a short-time working scheme (Steunpunt Werk based on RVA, 2021). Relative to a labor force of approximately 3 million people in Flanders, this constitutes a considerable share of 23%. Despite Belgium having the highest take-up of temporary unemployment in the financial crisis (Hijzen and Venn, 2011), the take-up was thus still higher in 2020. For an analysis of the impact of the furlough scheme during the financial crisis, see Van den bosch and Vanormelingen (2023).

In the context of the casual estimates in Section 3, we argue that the firms in the treatment group and in the control group both could benefit from the furlough scheme, such that the effect we pick up can be attributed to the Covid support mechanisms. To see whether the furlough schemes had a differential effect across treated and untreated, we control for the furlough scheme in the quarterly difference-in-differences estimation. We include a control variable $\frac{full\!-\!time\ equivalents_t}{number\ of\ workers_t} - \frac{full\!-\!time\ equivalents_{t-1}}{number\ of\ workers_{t-1}}$ as a measure of usage of the furlough scheme. The results of this regression are shown in Fig. 7. Although the point estimate for period 2 lies somewhat higher than in the baseline results, the coefficients reveal no significant differences, and both positive significant and persistent effects are virtually identical.

5.3. Alternative control groups

We also provide results with alternative control groups. A first exercise adds a matching procedure before running the quarterly event study. We therefore implement a nearest neighbor matching algorithm to find the firm that most closely resembles the treated firms among the firms that asked for support but did not obtain it. In particular, we match one-on-one using the Mahalanobis distance function as a scale-invariant distance metric. We perform matching without replacement, such that there is one unique match per treated firm. This avoids that the matching results might be driven by a few units in the control group that are repeatedly resampled. We match on two covariates: employment in FTE and capital as tangible fixed assets. Next, we conduct again the quarterly event study with the control group of nearest neighbors and show the results in Fig. 8. Again, the coefficients remain very similar to the baseline results.

[14] The mapping is not perfect, since there might be an adjustment in employee contracts from/to part-time employment.

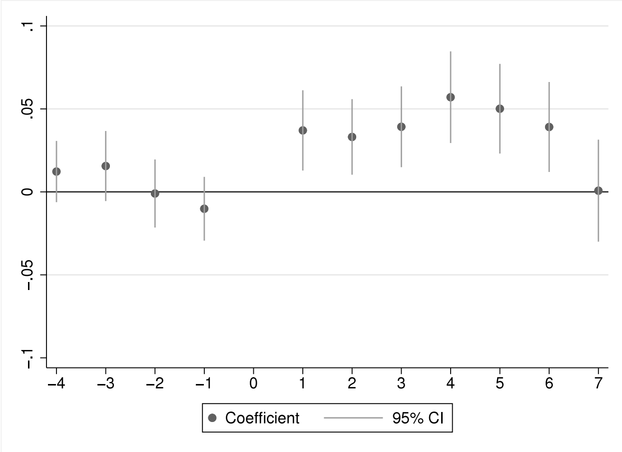

Fig. 7. Impact of support on labor productivity, quarterly diff-in-diff.
Notes: This figure shows the event study coefficients for the impact of support on labour productivity when controlling for the furlough scheme. Both firm fixed effects and industry-quarter fixed effects are included. Heteroscedastic robust standard errors are clustered at the firm level.

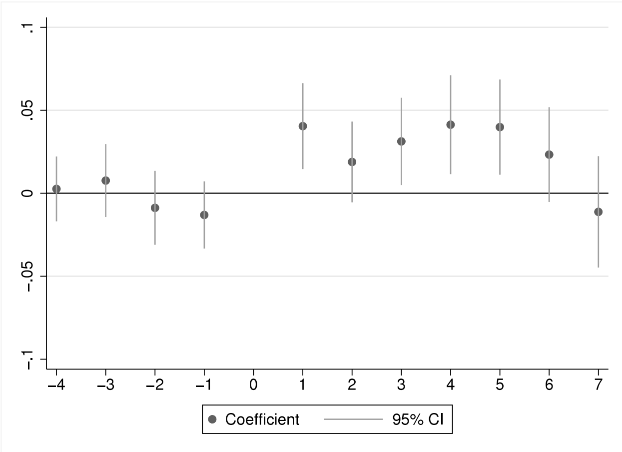

Fig. 8. Nearest neighbor matching results, quarterly diff-in-diff.
Notes: This figure shows the event study coefficients for the impact of support on labour productivity with a matched sample as control group. Both firm fixed effects and industry-quarter fixed effects are included. Heteroscedastic robust standard errors are clustered at the firm level.

A second robustness exercise using alternative control groups concerns the analysis of the impact of support on the propensity to exit. In Section 3, we include as a control group all firms that did not receive support, to construct a large enough set of exiting firms for meaningful estimates. However, when we include only firms that asked for support but did not get it as a control group as in the regression specification, the results do not change much. Table 9 shows the coefficients of the logit estimation. The coefficient for treatment is somewhat lower, but remains significantly negative and stable in all specifications. Furthermore, the marginal effect of receiving support derived from these coefficients suggests a very similar decline in the average exit probability of 0.6 percentage points, compared to the marginal effect of 0.5 p.p. found before.

5.4. Alternative estimator

In Section 3 we analyzed the impact of the Covid support mechanisms both using a static difference-in-differences specification for a yearly effect, and using a dynamic specification to allow for heterogeneous treatment effects across time for quarterly effects. We further explored heterogeneous treatment effects across firms by looking at the impact of different types of premia. The recent difference-in-differences literature has also brought forward methods to directly account for heterogeneous treatment effects across cohorts, i.e. groups of firms that receive support for the first time in the same quarter. We implement the estimation procedure of Sun and Abraham (2021). This estimator follows a three-step procedure. First, treatment effects are estimated separately for different cohorts, using the never-treated group of firms as a control group. Next, weights are estimated using the sample shares of

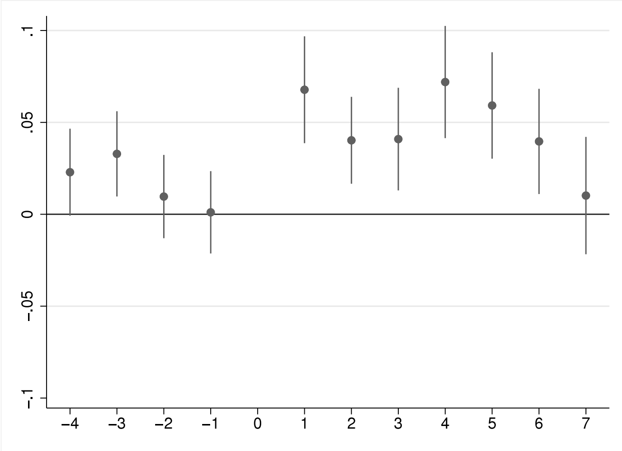

Fig. 9. Impact of support on labor productivity.
Notes: This figure shows the event study coefficients for the impact of support on labour productivity using the estimation procedure of Sun and Abraham (2021). Both firm fixed effects and industry-quarter fixed effects are included. Heteroscedastic robust standard errors are clustered at the firm level.

Table 9
Probability of exit, quarterly.

	Pr (exit)	Pr (exit)	Pr (exit)
Treatment D_{it}	−0.48***	−0.48***	−0.48***
	(0.14)	(0.14)	(0.14)
ln (value added/FTE)	−0.35***	−0.35***	−0.34***
	(0.03)	(0.03)	(0.03)
ln (FTE)	−1.03***	−1.03***	−1.02***
	(0.04)	(0.04)	(0.04)
debt/asset ratio 2019		0.09**	0.09*
		(0.04)	(0.05)
ln (age)			−0.21***
			(0.06)
Quarter fixed effects	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes
Pseudo R^2	0.17	0.17	0.18
N	47,981	47,981	47,981

Notes: Exit is a dummy variable which indicates whether a enterprise will exit in the next quarter. Heteroscedastic robust standard errors are clustered at the industry level. Significance: * <5%, ** <1%, *** <0.1%.

each cohort in the relevant periods. Finally, the average treatment effect on the treated firms by period are calculated as a weighted average based on the treatment effects of the first step and the weights of the second step. Fig. 9 shows the results. While one pre-period becomes borderline significant, the overall picture remains fairly similar to the results in the main text.

5.5. Diff-in-diff on productivity components separately

While we focus on the impact of firm-level support on firm-level productivity growth, we provide additional difference-in-differences results for the impact of these measures on sales, value added and employment separately. Table 10 shows the results of estimating Eq. (1) on these components. The resulting coefficients are an exact decomposition of the main results in Table 4. In particular, by the properties of OLS: $\beta_{\ln(\text{sales/FTE})} = \beta_{\ln(\text{sales})} - \beta_{\ln(\text{FTE})}$, or in this case $0.040 = -0.094 - (-0.134)$. Similarly for the coefficient on value added per FTE: $\beta_{\ln(\text{VA/FTE})} = \beta_{\ln(\text{VA})} - \beta_{\ln(\text{FTE})}$, or $0.047 = -0.087 - (-0.134)$. These results show that treated firms experienced a larger drop in both sales (or value added) and in FTE, but that the impact on FTE is slightly larger. This explains the within-firm positive productivity growth in Table 4, and also lines up with the decomposition of aggregate growth into value added and FTE in Fig. 4.

5.6. Aggregate productivity growth with structural TFP

Fig. 10 shows the results of the Melitz and Polanec (2015) aggregate productivity growth decomposition using total factor productivity (TFP), instead of labor productivity. TFP is estimated using the control function approach from Ackerberg et al. (2015). The details of the estimation procedure can be found in Appendix D. Aggregate productivity is measured as a weighted average of

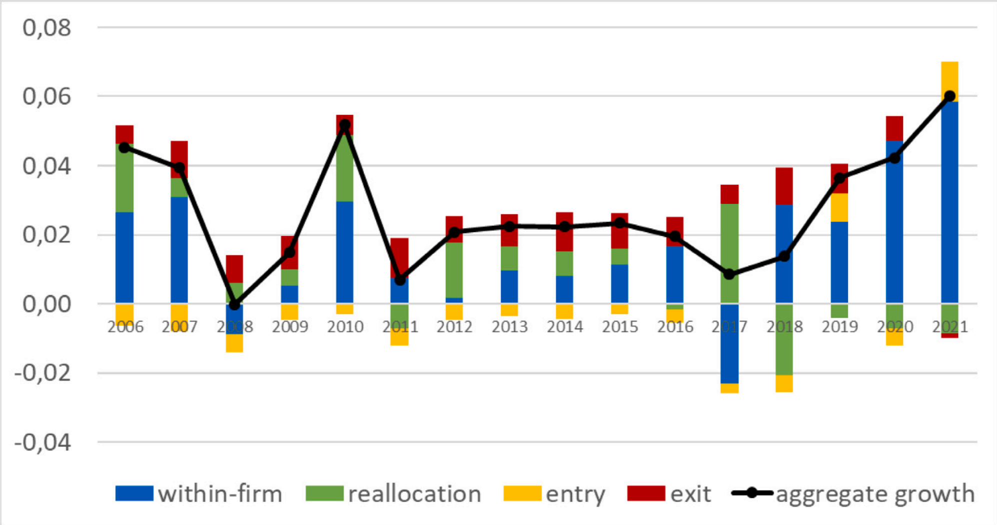

Fig. 10. Decomposition of aggregate productivity growth, structural TFP.

Table 10
Impact of support mechanisms on productivity components, annual.

	Ln (sales)	Ln (value added)	Ln (FTE)
Treatment D_{it}	−0.094***	−0.087***	−0.134***
	(0.012)	(0.015)	(0.013)
Industry-year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Adj. R^2	0.94	0.86	0.90
N	78,972	78,972	78,972

Notes: Heteroscedastic robust standard errors are clustered at the firm level. Significance: * <5%, ** <1%, *** <0.1%.

Table 11
Treated/untreated decomposition structural TFP growth.

Year	Gr. Agg. TFP Surv.	Treated: Av.	Treated: Cov.	Untreated: Av.	Untreated: Cov.	Between groups Cov.
2020	0.040	0.009	−0.012	0.038	−0.010	0.015
2021	0.050	0.036	−0.005	0.022	0.006	−0.010

firm-level TFP using employment weights. In 2020 aggregate TFP growth is 4.2%, which is a bit lower than the 5.9% using our labor productivity growth measure, but which is still in line with the general message that 2020 was characterized by positive aggregate productivity growth. The contrast with the financial crisis is again salient, with low TFP growth during the financial crisis. Within-firm productivity growth in both 2020 and 2021 was positive, while the covariance term was slightly negative in both years, similar to the labor productivity decomposition. Furthermore, the net entry effect (entry plus exit) contributed positively to the aggregate TFP growth in 2020, similar to what we found using labor productivity.

The aggregate productivity growth of surviving firms between 2020 and 2021 is further decomposed in groups of treated and untreated firms in Table 11. All terms have the same signs as before, and the ordering of the components is the same as in the labor productivity decomposition: the within-firm component is larger for treated firms than non-treated firms, there is a negative covariance component for treated firms and a positive one for untreated firms, and there is a negative between-groups component.

5.7. Alternative reallocation measures

Finally, we show some alternative measures of aggregate reallocation. To this end, we use job creation, job destruction and gross job reallocation measures as in Davis and Haltiwanger (1992). The growth rate in employment n is then defined as:

$$g_{it} = \frac{n_{it} - n_{it-1}}{x_{it}}$$

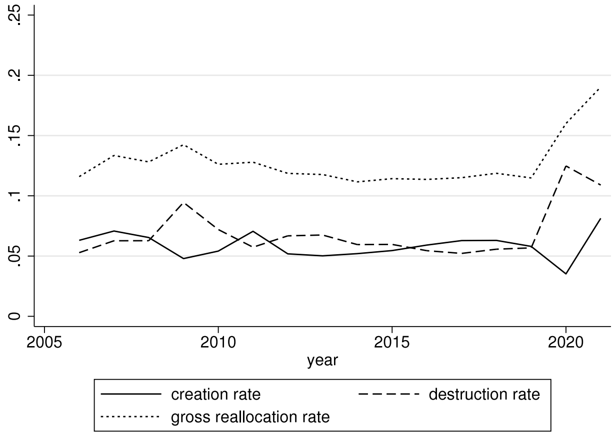

Fig. 11. Gross job reallocation.

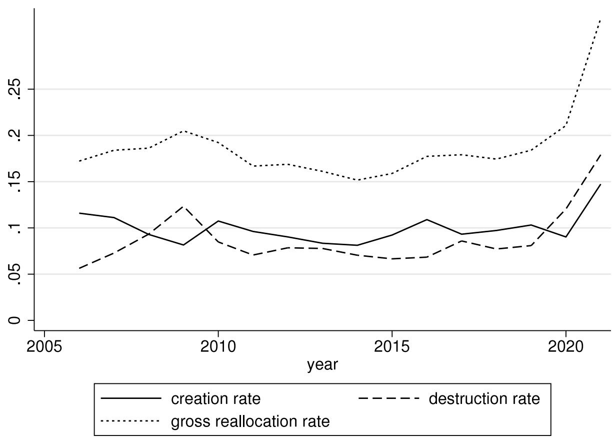

Fig. 12. Gross value added reallocation.

where x_{it} is the average employment over period t and $t-1$, $x_{it} = {}^{(n_{it}+n_{it-1})}/_{2}$. Because of the normalization, growth of surviving firms lies in the interval $[-2, 2]$. Job creation and job destruction rates are then defined as

$$POS_t = \sum_i \frac{x_{it}}{X_t} \cdot g_{it},\ \forall i:\ g_{it} > 0 \text{ and } NEG_t = \sum_i \frac{x_{it}}{X_t} \cdot |g_{it}|,\ \forall i:\ g_{it} < 0$$

where X_t is aggregate employment and x_{it} is a weight. Gross job reallocation is then the sum of job creation and job destruction. These three measures can also be implemented using value added instead of employment to examine the gross value added reallocation rate, analogously to sales measures constructed in Barrero et al. (2021). Fig. 11 shows how gross job reallocation increased a lot during the financial crisis, but even more so during the pandemic, reaching levels of almost 20%. This increase in job reallocation is mainly driven by the sharp increase in job destruction, which reached 10% in 2009, but even 15% in 2020 and 18% in 2021. We find a similar picture when we look at value added creation and destruction, with more value added reallocation in the pandemic in Fig. 12. There has thus been a lot of reallocation in 2020 and 2021, but earlier results have shown that it has not benefited aggregate productivity. Apparently, the reallocation driven by the Covid-19 crisis does not adhere to the expected reallocation according to the productivity distribution.

6. A discussion on potential mechanisms

6.1. The intervention logic and identification strategy revisited

With the global outbreak of Covid in March 2020, governments in many countries imposed emergency policies to curb the spread of the virus, including lockdowns, social distancing, and industry closures.[15] These forced closures induced massive market failures, as many local and global markets unexpectedly shut down in a matter of days. To flank the emergency sanitary measures, and to attenuate induced losses to enterprises, many governments implemented firm-level support schemes (see OECD (2021) for an overview). In Belgium, national and regional governments issued a series of support measures for enterprises, including moratoria on bankruptcies, furlough schemes, financial instruments, and direct subsidies. See Appendix B for a detailed description of the various policies, and a timeline of the lockdown policies and tandem support measures for enterprises.

Our focus in this paper is on the VLAIO support measures and their impact on firm-level and aggregate outcomes in terms of productivity and firm exit. The goal of these particular support measures was to keep the economy afloat by allowing enterprises to keep making essential payments, to retain productive capacity, and to avoid firm failures, layoffs, and liquidity issues as a direct result of the sanitary policies that had been implemented. At the macro level, these support measures were indented to attenuate the resulting economic crisis and to accelerate economic recovery afterwards (Zegel et al., 2021).

Since several measures co-existed, our goal is to isolate the impact of the VLAIO support mechanisms on enterprise-level and aggregate outcomes from these alternative measures. Specific to this support program is that enterprises had to be eligible for support based on sector- and firm-level criteria. This is different from the other policies such as the moratoria on bankruptcies and furlough schemes, which were available to all enterprises during this period and which firms could self select into. The specificity of the VLAIO mechanisms allows us to exploit variation in outcomes across enterprises that obtained this support and those that are very similar but did not receive this support.

In our baseline difference-in-differences strategy in Section 3, we compare outcomes both within firms over time and with firms that applied for, but did not obtain, VLAIO support. We show that potential non-random selection into treatment (e.g. enterprises that were rejected because they could remain open, or faced smaller drops in turnover than those in the treated group) would in fact attenuate the difference in means across both groups, and if anything, bias downwards our estimates of the true impact of the support measures on firm outcomes. We validate the three key assumptions to obtain causal estimates from the regression setup: (i) the parallel trends assumption, (ii) no anticipation effects, and (iii) the stable unit treatment value (SUTVA) assumption. Identification relies on parallel trends in the average growth rate of productivity across firms in both groups. In Appendix C, we show additional supportive evidence on the full distribution of pre-period productivity growth rates and their common support across the whole distribution.

To further corroborate the potential differential effect of other concurrent policies, we provide additional robustness checks in Section 5. We explicitly control for the use of the federal furlough schemes across both treated and untreated firms. We provide a placebo test to investigate whether we are picking up other effects than those of the policy, and we provide results with a control group of other Flemish firms that are similar but did not apply for VLAIO support using nearest-neighbor matching.

All results point in the same direction: enterprises that received VLAIO support see an increase in labor productivity and a decrease in the probability to exit the market. Moreover, the impact on productivity growth seems to be temporary: by the end of 2021, supported firms are no longer statistically different from non-supported firms in terms of firm outcomes. Still, it is possible that the causally identified effects might relate to various alternative hypotheses on the impact of these support measures on firm-level outcomes. In this section, we discuss various potential mechanisms by combining information on (i) in-depth interviews with enterprises that received VLAIO support, (ii) economic theory, (iii) and similar policies and outcomes in other countries.

6.2. Results from in-depth interviews

In the context of the VLAIO support mechanisms, Technopolis Group has executed several in-depth interviews with business associations, sectoral umbrella organizations, individual enterprises, and other relevant actors. A subset of questions related to the perceived effects of the VLAIO support measures on sector- and enterprise-level outcomes, including turnover, fixed costs, employment, financing structure, liquidity and solvability, the probability of exit and future expectations. We summarize answers to these questions here. More details on the methodology, as well as verbatim responses can be found in Zegel et al. (2021).

Respondents replied that most enterprises saw a large reduction in turnover, with sizable variation across sectors and individual firms. The main use of the support measures is reported to cover fixed costs such as rents, energy, leases and personnel. However, larger firms acknowledged that the first premium (flat fee) was often not sufficient to cover such costs. Later mechanisms provided support as 7.5 to 10% of turnover in a reference period in 2019, and larger firms confirmed that these mechanisms were better in line with their fixed costs structures. This is also in line results in Bormans and Konings (2020), who find that most NACE 2-digit industries in Belgium have fixed costs in the order of 10%–20% of turnover in normal times. Yet, smaller enterprises favored the initial flat fee premia over the ad valorem premia, as the burden of proof for the sales decline was a greater barrier for them. Moreover, some enterprises replied that they experienced large drops in turnover, close to, but smaller than 60% with respect to the reference period. Not obtaining the support in this case felt unfair to them.

[15] See the Oxford Covid-19 Stringency Index, providing detailed information on these policies implemented by country and by date.

When asked about the impact on employment, respondents agree that the federal furlough schemes had provided the largest safety net to retain workers at the firm. Additional effects of the VLAIO policies include coverage of remaining employment costs, such as keeping some highly wanted employees fully on board, instead of falling back to 70% of their wage through furlough schemes. Some enterprises mention that they had re-evaluated what activities were still possible during the first and second lockdowns in 2020, and developed alternative delivery of goods and services, such as take-away for restaurants, opening or expanding a web shop, online events in the cultural sector etc. Such alternatives often required fewer workers to operate, such as no waiters, less technical personnel, and less cleaning services. Various respondents suggested that these lockdowns allowed to evaluate their existing processes and activities, and to consider opportunities for new sources of revenue, where they lacked time for such strategic thinking in normal times. On the other hand, many industries often rely on pre-determined contracts, that require upfront payment and investments, even if projects or deliveries are canceled, such as organizers for large events. In terms of equity, some had used the support to increase their equity, to improve solvency, or to improve the probability of getting a loan later on if it would turn out to be needed. Many reply that the enterprise would have probably survived without these support measures, but that this would have had a sizable impact on their debt or equity. Still, most reported that financial buffers were depleted by the end of 2020, and that another wave of lockdowns would have pushed them into insolvency, especially for smaller firms that have less opportunities for external financing than larger firms. In general, respondents were highly uncertain about the future, in terms of their own potential survival and growth, and how markets might change when the economy opened up again. Uncertainty on market demand post-Covid was especially high in business-to-consumer markets, such as personal services and retail. Yet, enterprises very much appreciated the swift support by the governments, and this also contributed to mental support and the feeling that enterprises were not left alone.

The intervention logic and responses from interviews underline that the goal and use of the VLAIO support measures was much broader than only avoiding firm exit. While we do not have quantitative data to further corroborate these findings, respondents mention that the support measures had been used as intended: to cover fixed costs, to keep personnel, to avoid liquidity and solvency issues and to overcome the highly uncertain periods of lockdowns and (partial) reopening of the economy.

6.3. Potential mechanisms

Our results show that supported enterprises experienced a significant increase in productivity and a reduction in the probability to exit the market. How do these results relate to economic intuition?

Generally, the imposed sanitary restrictions clearly affected the existence and size of markets for various goods and services. If markets collapse, the demand for factors of production such as labor or capital decreases drastically. Still, firms need to be able to cover their fixed costs, such as rents, machinery, leases etc. Failure to cover these costs increases the probability of exiting the market due to increased solvency and liquidity risks. As discussed in the intervention logic, avoiding exit was one of the goals of the support program. Our results suggest that the probability of exit indeed decreases sharply for supported firms, conditional on typical covariates that predict exit. The interviews also mention that at least a fraction of enterprises have indeed used the support to pay fixed costs and to increase capital buffers. Studying the impact of similar Covid-19 support measures for the Netherlands, Davies et al. (2023) find that support reduced the overall exit rate of companies by 16% in 2020. These findings jointly suggest that such support schemes have at least alleviated such constraints that could trigger firm exit.

We also find that supported enterprises saw a larger increase in labor productivity than non-supported firms. What is the source of these productivity increases? When we decompose aggregate productivity growth into its components value added and labor in Fig. 4, we see that both value added and labor use drops in 2020. The drop in labor is larger however, generating a positive productivity growth: output per employee increases, even if aggregate output drops. In 2021, both components recover, with a sharp increase of labor use, suggesting temporary effects on labor. At the micro level, we see in Table 10 that both output (measured in sales or value added) and FTE drop, but both components drop more for treated firms than untreated firms. This suggests that output per worker for treated firms increases mostly due to a more than proportional reduction in labor.

These findings are consistent with economic theory. First, as the demand for output drops, the demand for labor as an input to production also drops. Labor might be either a fixed or a variable cost, depending on various factors such as temporary versus permanent employment contracts, worker protection laws etc. If labor is a variable cost, enterprises can scale back production to meet demand, and avoid paying excess labor costs. In this case, support might be used for any of the other purposes discussed above, such as capital buffers, creating an online sales platform etc. When demand conditions improve, the firm might increase labor inputs again, consistent with the results in Fig. 4. These choices are consistent with per period cost minimization and profit maximization from the point of view of the firm. The impact on aggregate welfare is a priori not clear however, and depends on the relationship between the changes in real wages and consumption.

Alternatively, labor is a fixed cost, and enterprises have to keep paying these costs independent of the level of output. In the short run, fixed costs are sunk, and firms face the decision to either continue operating, or to shut down production. As long as revenues are greater than the variable costs of production, it chooses to operate. Whenever revenues are less than variable costs, it is optimal to shut down production, pay the fixed costs, and incur losses that are equal to the size of the fixed costs. Enterprises might then use the financial support to pay for these fixed costs. If market conditions improve again, due to increases in demand or lower marginal costs, firms might start operating again and earn positive profits. This is also consistent with what we see in the aggregate from 2020 to 2021. If positive profits are not attainable in the long run however, the firm exits the market. This economic intuition was also part of the intervention logic of the later support instruments: enterprises received an *ad valorem* support between 7.5%–10% of turnover in normal times.

Second, we do see that supported firms reduce labor more than non-supported firms. This makes sense: treated firms faced larger reductions in sales or were forced to close down, and thus had to reduce factors of production more than non-treated firms. Firms could have used support to cover fixed labor costs. While we do not observe the use of the financial support within the firm, the interview responses suggest that the support was used to keep some key personnel fully on board, and to minimize the risk of such employees leaving the company either through temporary unemployment, or outright separation. These responses also hint at potential heterogeneity in worker quality: firms might want to keep the best employees, which are either more efficient in a given task, or can handle new additional tasks, thus increasing labor productivity per employee.

Finally, are these productivity increases sustainable in the long run? Several arguments point towards "No". First, the work environment was particularly insecure, especially for workers with temporary contracts, women and mothers. Work pressure has been perceived as high, and burnout rates skyrocketed in 2020 (Abramson, 2022). Second, we do find that the initial productivity gains revert back both in the aggregate Fig. 4 and at the firm-level Fig. 3. This is mostly driven by a recovery in FTEs in 2021. Third, if capacity utilization was optimized before Covid, such a significant shock to output levels and input use would imply that *ex post*, capacity utilization should be sub-optimal. Conversely, if capacity utilization is assumed to be maximized *ex post*, this would suggest that it was not optimal before going into the crisis.

Some arguments also point towards "Yes". First, reoptimizing the firm's labor force in response to the shock can be efficiency improving, due to either improvements in capacity utilization or sorting of worker quality. Even in the absence of labor reshuffling, a shift to teleworking can improve productivity in the long run (OECD, 2020a). The support mechanisms could have contributed to investments in the necessary hardware, software and organizational restructurings to allow for working from home. Second, firms had to find new ways to sell their products or services, both to provide a safe way to provide delivery, as well as to cope with shifts in consumer demands, also after the economy reopened. Interview respondents also mention the possibilities to use the support to invest into new forms of delivery of goods and services, such as increased take-out options, and online sales platforms. This argument is consistent with recent findings by Harasztosi et al. (2022): using EU-wide information from European Investment Bank surveys, they find that obtaining policy support increases the probability of raising overall investment. In terms of digital investments, supported firms digitalized by 5% more.

7. Conclusion

In this paper, we have studied the impact of firm-level Covid-19 support mechanisms on both firm-level and aggregate productivity growth, exit and creative destruction. To this end, we have combined administrative data on the universe of firms' support in Flanders with firm-level operational information on employment and sales. Firms that received support increased productivity by 4%–5%, compared to firms that applied for, but did not obtain support. This effect was persistent up to six quarters after treatment, after which it washed out on average. Support measures also reduced firm failure. The propensity to exit the market was 45% lower when a firm received support. There is variation in both the nature and scope of the individual support schemes. When estimating the impact of the individual support schemes, we find that the first premium had the largest effect on firm-level productivity growth, compared to the other four measures. The first premium was the largest in terms of total amount allocated, and also the largest on average per firm in absolute terms. This was especially helpful for smaller firms, as it provided a larger percentage support relative to the size of the firm. The intuition behind this is that it allowed especially small firms to cover their fixed costs, which was also confirmed in a number of individual interviews that were conducted. Thus the support policies achieved their main goals: to keep the economy afloat in response to the massive sanitary restrictions.

In the aggregate, within-firm productivity growth was similar for both supported firms and firms not receiving Covid support. But there was a reallocation of market shares from the former to the latter. There are signs of insufficient creative destruction on both the extensive margin (firm entry and exit) and intensive margin (reallocation of market shares to more productive firms) during the crisis. However, insufficient reallocation was already present well before the crisis, and there is no evidence that this inefficiency is driven by the contribution of treated firms in particular.

Taken together, our results suggest that Covid rescue policies helped firms to avoid exit and to temporarily increase productivity, while not significantly distorting the process of creative destruction in the aggregate. More generally, the results suggest that industrial policy can be effective when it is well targeted, limited in time and designed in a way that takes into account the specific demand and cost constraints firms face.

Appendix A. Description of NACE sectors

Table 12 shows a description of the 2-digit NACE codes (Rev. 2, 2008) and their aggregations for sparse sectors in the TFP estimation, and a verbal description of these sector activities.

Appendix B. Government support measures

In this section, we provide a detailed timeline of the lockdown policies and tandem support measures for enterprises that we study in this paper. We also describe the other concurrent support measures issued by the Belgian and Flemish governments.

The Covid-19 pandemic started spreading widely throughout Europe in the beginning of March 2020. As a consequence, the Flemish government together with the Belgian federal government installed safety measures, including closing down businesses from March 13 onwards. To support these businesses and attenuate the economic impact of the Covid crisis, the Flemish government

Table 12
NACE industry descriptions.

Industry code NACE Rev. 2	Description	Industry code NACE Rev. 2	Description
1	Crop and animal production, hunting and related service activities	45	Wholesale and retail trade and repair of motor vehicles and motorcycles
2	Forestry and logging	46	Wholesale trade, except of motor vehicles and motorcycles
3	Fishing and aquaculture	47	Retail trade, except of motor vehicles and motorcycles
5–9	Mining and quarrying	49	Land transport and transport via pipelines
10	Manufacture of food products	50	Water transport
11–12	Manufacture of beverages and tobacco products	51	Air transport
13	Manufacture of textiles	52	Warehousing and support activities for transportation
14	Manufacture of wearing apparel	53	Postal and courier activities
15	Manufacture of leather and related products	55	Accommodation
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	56	Food and beverage service activities
17	Manufacture of paper and paper products	58	Publishing activities
18	Printing and reproduction of recorded media	59	Motion picture, video and television programme production, sound recording and music publishing activities
19–21	Manufacture of coke, refined petroleum products, chemicals and chemical products, basic pharmaceutical products and pharmaceutical preparations	60	Programming and broadcasting activities
22	Manufacture of rubber and plastic products	61	Telecommunications
23	Manufacture of other non-metallic mineral products	62	Computer programming, consultancy and related activities
24	Manufacture of basic metals	63	Information service activities
25	Manufacture of fabricated metal products, except machinery and equipment	64–66	Financial and insurance activities
26	Manufacture of computer, electronic and optical products	68	Real estate activities
27	Manufacture of electrical equipment	69	Legal and accounting activities
28	Manufacture of machinery and equipment n.e.c.	70	Activities of head offices; management consultancy activities
29	Manufacture of motor and vehicles, trailers and semi-trailers	71	Architectural and engineering activities; technical testing and analysis
30	Manufacture of other transport equipment	72	Scientific research and development
31	Manufacture of furniture	73	Advertising and market research
32	Other manufacturing	74	Other professional, scientific and technical activities
33	Repair and installation of machinery and equipment	75	Veterinary activities
35	Electricity, gas, steam and air conditioning supply	77	Rental and leasing activities
36–39	Water supply; sewerage, waste management and remediation activities	79	Travel agency, tour operator reservation service and related activities
41	Construction of buildings	80	Security and investigation activities
42	Civil engineering	81	Services to buildings and landscape activities
43	Specialized construction activities	82	Office administrative, office support and other business support activities

responded with an extensive support scheme. A timeline of the measures taken in 2020 is given in Fig. 13. On the left is an overview of the safety measures. The most stringent lockdown was enforced mid March and lasted until mid May. After that, several sectors were still hindered in their activities. The summer did bring some relief and mostly in July, most businesses were reopened. Exceptions to this rule were large events and nightclubs. General safety measures regarding gatherings remained in place during the months of August and September, but a real lockdown was imposed in October again, which lasted until December of 2020. On the right is an overview of the VLAIO firm-level support measures taken by the Flemish government. From the very beginning of the safety measures, firms got the opportunity to file for government support to compensate for suffered losses. The government has rolled out six different support programs in the course of 2020. The sixth measure covered the period November 16 to December 31, 2020, but its payout only started in 2021. We study the impact of the five support measures paid out in 2020, which are described in detail in Table 1.

During the period that the VLAIO support mechanisms were in place, other regional and federal support schemes for enterprises existed. These include moratoria on bankruptcies, furlough schemes, and financial instruments.[16]

Moratoria on bankruptcies. At the onset of the pandemic, the fear of major economic fall-out was real. Early on, OECD (2020b) reported that without government intervention, especially small and medium enterprises would face a drastic increase

[16] Other smaller and tangent support mechanisms existed at the national, regional and municipal level. For a complete overview, see here (only in Dutch). The federal Audit Court also provides an inventory, intervention logic and audit of all federal measures here.

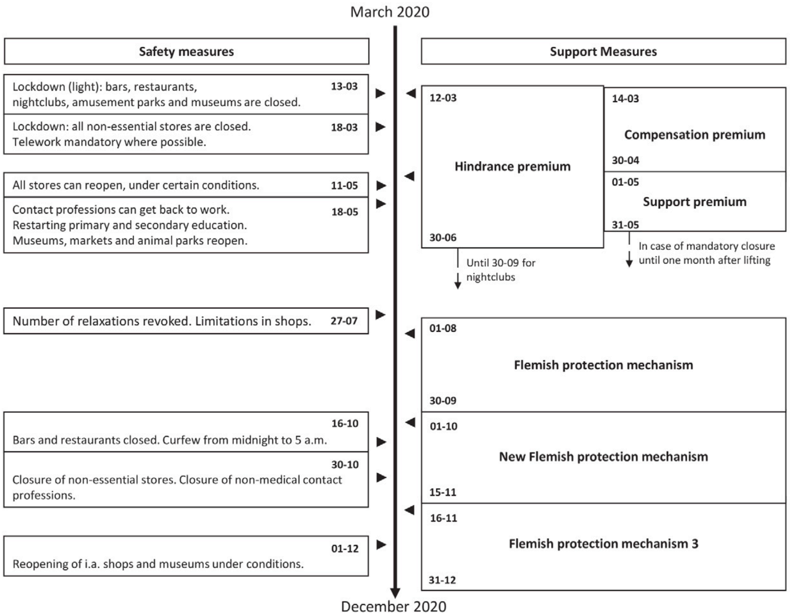

Fig. 13. Timeline of Covid-19 safety and support measures in 2020.

in the probability of failure due to the effects of long-term closures. Between April 24, 2020 and January 31, 2021, the Belgian government issued moratoria on bankruptcies. Any enterprise that was financially healthy before March 18, 2020 (i.e. faced no liquidity issues up to that date), was temporary protected from its creditors. Courts would not trigger defaults in this case, except for fraudulent failures. *Ex post*, the number of bankruptcies in 2020 and 2021 are the lowest since the financial crisis in 2008. This is mainly due to the moratoria on bankruptcies.[17] Additional measures, such as the VLAIO support mechanisms and other supplementary measures at the national level have further attenuated the number of failures.

Furlough schemes. In Belgium, the system of temporary unemployment was already in place for certain exceptional situations before Covid-19. Enterprises can apply for compensation for their employees in case of force majeur or economic circumstances. If approved, employees receive 65% of their gross wage, which is paid by the social security system rather than the firm. This allows companies to recover financially by avoiding these labor costs, while employees remain at the company without ending the employment contract, and are certain of reactivation when the enterprise's circumstances improve. Between March 18, 2020 and June 30, 2022, enterprises could apply for an enhanced version of this policy, where 70% of wages was covered, and with a simplified and more lenient application. Moreover, companies could apply for installment plans for up to 24 months at the Social Security. This program was by far the largest policy in terms of budgetary impact, with a cost of 5.6 billion euro between March 2020 and June 2021.

Financial instruments. Governments also implemented various financial instruments, such as loans and bank guarantees. Non-financial enterprises that had no payment arrears or were not undergoing active credit restructuring on January 31, 2020, could obtain a state guarantee for newly contracted loans with a maturity of up to 12 months from April 1, 2020. The federal government was guarantor for up to 50 billion euro with the Belgian banks. Additional instruments included bridging guarantees, 6-month payment extension for companies and others.

Appendix C. Additional descriptive statistics

This section provides additional information on descriptive statistics reported in Section 2. Table 13 shows the distribution of employment, expressed in FTEs, by high-level industry for the year 2019, for the sample of analysis used in the aggregate growth decomposition. As is typical for post-industrialized economies, market services account for the vast majority of both the number of enterprises and the number employed people, followed by manufacturing. These patterns also line up with the aggregate contribution of services and manufacturing to the Flemish economy. In 2019, services accounted for 70% of Flemish GDP and 45% of total employment, while manufacturing accounted for 16% of Flemish GDP and 12% of total employment. Over 80% of the working population is enrolled as employee.

[17] It is important to note that official statistics on firm failures can arrive with significant delay, due to the time gap between effective cessation of activities of the enterprise, and the official bankruptcy declaration by courts. We define exit based on no longer reporting mandatory social security statements.

Table 13
Distribution of employment (FTE) by high-level industry (2019).

Industry	Total FTE	Number of enterprises	Mean	Std. dev.	Percentiles		
					p10	p50	p90
Primary and extraction (NACE 01-09)	12,928	1,219	10.6	25	0.7	3.7	25
Manufacturing (NACE 10-33)	258,917	7,812	33.1	146	1	5.7	60
Utilities (NACE 35-39)	19,183	393	48.8	237	1	6.8	61
Construction (NACE 41-43)	97,950	12,517	7.8	29	0.7	2.5	15
Market services (NACE 45-82)	560,737	52,529	10.7	85	0.6	2.6	18

Table 14
Summary statistics treated versus never treated, sector demeaned (2019).

	Variable	Mean	Std. dev.	*Percentiles*		
				p10	p50	p90
Treated (N = 23,049)	Ln Employees (FTE)	0.0	1.3	−1.5	−0.1	1.6
	Ln Employees (head count)	0.0	1.1	−1.2	−0.1	1.4
	Ln Value added	0.0	1.2	−1.5	−0.1	1.5
	Ln Turnover	0.0	1.2	−1.3	−0.1	1.4
	Ln (Value added/FTE)	0.0	0.7	−0.7	−0.1	0.7
	Ln (Turnover/FTE)	0.0	0.9	−0.9	−0.1	1.1
Untreated (N = 3,275)	Ln Employees (FTE)	0.1	1.2	−1.3	0.0	1.7
	Ln Employees (head count)	0.1	1.1	−1.1	0.0	1.6
	Ln Value added	0.2	1.3	−1.3	0.1	1.7
	Ln Turnover	0.1	1.3	−1.4	0.0	1.7
	Ln (Value added/FTE)	0.1	0.7	−0.6	0.0	0.9
	Ln (Turnover/FTE)	0.0	0.9	−1.0	−0.1	1.0

Notes: Employment is expressed as the firm-level number of full-time equivalents (FTE), averaged over quarterly values in 2019; value added and turnover are the totals in euros over 2020. p10, p50 and p90 indicate the 10th, 50th (median) and 90th percentiles. All variables are depicted in logarithmic values and demeaned by NACE 2-digit industry averages.

Table 14 shows the summary statistics of *treated* and *never treated* firms for the year 2019, in natural logs, and demeaned at the NACE 2-digit industry level. Within sectors, treated enterprises are slightly smaller than untreated enterprises on average, while all other moments are quasi identical, and with a common support across the whole distribution.

Fig. 14 shows the full distribution of productivity growth of both *treated* and *never treated* enterprises before Covid, calculated as the log difference between the first and the last quarter of 2019. We calculate the growth rate over this period to avoid any potential impact of Covid-19 on firm outcomes in the first quarter of 2020. Since we calculate this using quarterly data within a year, we cannot provide similar growth rates using value added or value added labor productivity, which relies on annual accounts data. Across all variables, both treated and never treated exhibit significant overlap in growth grates across the whole distribution.

Appendix D. TFP estimation

Total factor productivity (TFP) for firm i in year t can be estimated as the residual of a production function, for which a functional form has to be specified. As is standard in the literature, the Cobb–Douglas form of the production function is used. In logarithms:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \varepsilon_{it}$$

where y_{it} is the log of value added, log capital is k_{it} and labor l_{it}. The value added production function can be seen as a gross output production function that is Leontief in intermediate inputs (Gandhi et al., 2020). The unobserved component is broken down into two terms, ω_{it} en ε_{it}. These two terms together encompass all shocks to output that are not explained by changes in labor or capital. They are both unobserved to the econometrician. Where ω_{it} is observed by the firm, ε_{it} is unobserved to the firm as well before making its input decisions. That the firm observes the realization of the shock ω_{it} to its production, means it can base their other input choices on this realization. Since the shock is unobserved to the econometrician, it will appear in the error term, creating an endogeneity problem (Marschak and Andrews, 1944). Indeed, labor and capital will be correlated with the ω_{it} term.

To estimate the production function, we use the methodology proposed by Ackerberg, Caves and Frazer (ACF) (2015). The methodology fits into the large strand of literature that estimates production functions using the control function or semi-parametric estimation approach, an idea first introduced by Olley and Pakes (OP) (1996). They derived the identification of production functions from a dynamic model of firm behavior allowing for idiosyncratic uncertainty and specifying the information available when input decisions are made. They suggested to account for productivity ω – observed to the firm, unobserved to the econometrician – using an inversion with investments as a proxy variable. We will nevertheless use intermediate inputs as a proxy variable to take into consideration the critique given by Levinsohn and Petrin (LP) that investments are often zero or lumpy reported (Levinsohn and Petrin, 2003).

The ACF methodology firstly uses an intermediate input function of the form $m_{it} = f_{it}(\omega_{it}, k_{it}, l_{it})$. Observed productivity can then be inverted out. The implicit assumption is that intermediate inputs are a deterministic function of observed productivity, capital and

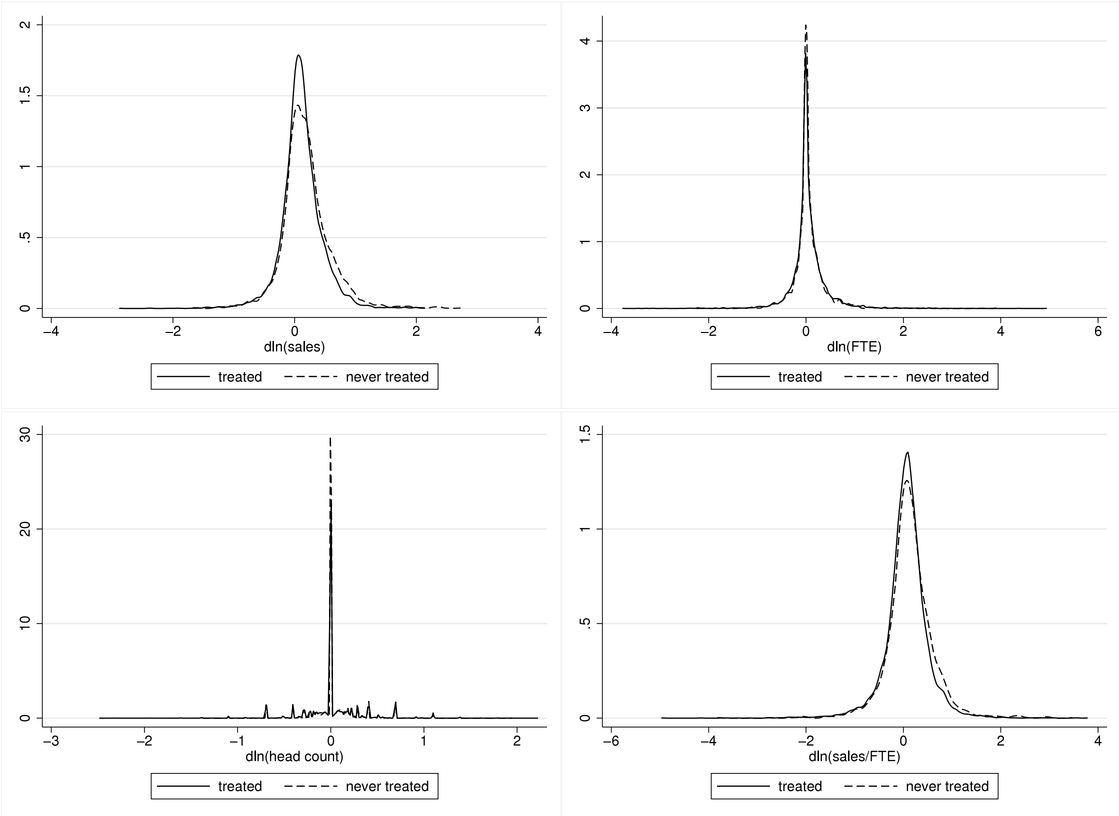

Fig. 14. Distribution of growth rates treated versus never treated (2019).
Notes: Growth rates are expressed as log-differences in values between 2019q1 and 2019q4.

labor and that the function must be strictly monotonic in productivity. ACF depart from the preceding literature in the formulation of the proxy variable function. They argue that the OP and LP methodologies may suffer from functional dependence problems regarding labor, and therefore include labor in the intermediate input function and refrain from estimating the labor coefficient in a first stage. Secondly, productivity is considered to follow a dynamic process characterized by $E(\omega_{it}|\,\omega_{it-1},\ldots,\omega_{i1}) = E(\omega_{it}|\,\omega_{it-1})$, or, where ξ_{it} is the innovation in observed productivity.

The ACF methodology proceeds to estimation in two stages. In the first stage, they plug the inverted demand function for intermediate inputs into the production function:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + f^{-1}(m_{it}, k_{it}, l_{it}) + \varepsilon_{it}$$

No coefficients are estimated in this first stage, but it is used to net out the unobserved productivity term ε_{it}. So one obtains an estimate of the term $\theta(m_{it}, k_{it}, l_{it}) = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + f^{-1}(m_{it}, k_{it}, l_{it})$ as a third order polynomial. This estimate can then be used in a second stage. Together with the characterization of the productivity process, the production function can be reformulated as follows:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + g(\hat{\theta}_{it-1} - \beta_0 - \beta_k k_{it-1} - \beta_l l_{it-1}) + \xi_{it} + \varepsilon_{it}$$

The goal is then to estimate both the labor and capital coefficient β_l and β_k to retrieve productivity $(\omega_{it} + \varepsilon_{it})$ as the residual $y_{it} - \beta_k k_{it} - \beta_l l_{it}$. These coefficients are estimated in a generalized method of moments procedure using moment conditions that will be discussed next. The composition of function $g \circ f^{-1}$ is again approximated using a third order polynomial. Variables in previous periods are assumed not to be correlated with the innovation in productivity ξ_{it}. The standard timing assumptions in the literature that allow estimation take capital as a state variable and allow labor to be variable. On the one hand, capital is decided upon one period before, such that it is not correlated with the innovation in productivity. On the other hand, labor can be more variable and may be adjusted as a reaction to a positive productivity shock. That means that labor needs to be instrumented, as usually by the lag of labor. The sample analogs of the following moments are used in the GMM estimation procedure:

$$E\left\{ \left(\xi_{it} + \varepsilon_{it}\right) \begin{pmatrix} k_{it} \\ l_{it-1} \end{pmatrix} \right\} = 0$$

Table 15
Production function coefficients (2005–2020).

Industry	β_l	β_k	Avg. ln (TFP)	Avg. ln (labor prod)	Industry	β_l	β_k	Avg. ln (TFP)	Avg. ln (labor prod)
1	0.62	0.15	9.74	11.30	45	0.83	0.11	10.25	11.34
2	0.56	0.22	9.10	11.59	46	0.90	0.05	11.08	11.52
3	1.05	0.03	11.36	11.79	47	0.74	0.12	10.06	11.21
5–9	0.14	0.21	10.40	12.02	49	0.80	0.11	10.30	11.30
10	0.82	0.11	10.16	11.25	50	0.76	0.18	9.88	11.98
11–12	0.50	0.17	10.46	11.71	51	0.78	0.09	10.88	11.60
13	0.73	0.09	10.53	11.17	52	0.83	0.09	10.84	11.58
14	0.59	0.08	10.60	10.97	53	0.83	0.09	10.39	11.16
15	0.90	0.09	10.12	11.07	55	0.62	0.16	9.74	11.41
16	0.78	0.09	10.43	11.24	56	0.66	0.11	10.07	11.15
17	0.87	0.06	10.89	11.35	58	0.76	0.03	11.27	11.32
18	0.74	0.09	10.52	11.30	59	0.79	0.06	11.03	11.50
19–21	0.99	0.07	10.75	11.70	60	0.56	0.04	11.97	11.57
22	0.83	0.11	10.38	11.36	61	1.29	0.06	10.48	11.39
23	1.15	0.07	10.21	11.40	62	0.88	0.04	11.08	11.38
24	0.68	0.13	10.58	11.47	63	1.18	0.02	10.93	11.34
25	0.80	0.09	10.55	11.33	64–66	1.17	0.04	11.12	11.64
26	1.01	0.06	10.67	11.49	68	0.21	0.14	10.32	11.87
27	0.67	0.08	11.04	11.32	69	0.80	0.07	10.92	11.61
28	0.93	0.07	10.66	11.40	70	0.47	0.09	10.95	11.71
29	0.95	0.06	10.71	11.32	71	0.81	0.08	10.75	11.48
30	1.01	0.07	10.61	11.47	72	0.97	0.08	10.68	11.61
31	0.74	0.11	10.16	11.12	73	0.85	0.06	10.79	11.36
32	0.79	0.10	10.38	11.25	74	0.78	0.09	10.45	11.32
33	0.79	0.07	10.83	11.39	75	0.66	0.12	10.42	11.77
35	0.22	0.19	11.17	12.59	77	0.42	0.22	9.56	11.79
36–39	0.18	0.16	11.05	11.64	79	0.86	0.07	10.52	11.16
41	1.46	0.02	10.69	11.38	80	0.77	0.07	10.73	11.24
42	0.79	0.10	10.54	11.40	81	0.76	0.10	10.43	11.42
43	0.78	0.09	10.44	11.31	82	0.73	0.07	10.84	11.48

Table 16
Impact of support measures on productivity, pre/post with year fixed effects.

	ln (sales/FTE)	ln (value added/FTE)
Treatment D_{it}	0.058***	0.075***
	(0.011)	(0.012)
Year fixed effects	Yes	Yes
Firm fixed effects	Yes	Yes
Adj. R^2	0.81	0.59
N	78,972	78,972

Notes: Heteroscedastic robust standard errors are clustered at the firm level. Significance: * <5%, ** <1%, *** <0.1%.

The labor and capital coefficients are estimated by sector for the period under consideration, 2005–2020. Both stages of the estimation procedure include year fixed effects to control for yearly differences. Table 15 shows the estimated coefficients and resulting average productivity estimates. The average labor productivity is also included. Productivity measures are normalized with the average productivity in the industry that is depicted hereafter, such that β_0 is dropped (Van Biesebroeck, 2008).

Appendix E. Additional results

In Section 3, we estimate the pre/post impact of support measures using industry-year fixed effects. This setup allows to capture heterogeneity in sector-level trends in outcomes. Table 16 shows results using the standard canonical TWFE estimation with only firm and period fixed effects. The main estimated coefficients are then larger, at 5.8% and 7.5% respectively.

Table 17 reports the numbers underlying the main decomposition of aggregate labor productivity growth in Fig. 5. Similarly, Table 18 reports those for structural TFP growth in Fig. 10.

In Section 4, we decompose aggregate productivity growth into several components. That analysis is for the entire Flemish economy, aggregated across all economic sectors. In Tables 19 and 20, we perform this decomposition for manufacturing (NACE 10–33) and services (NACE 35–82) separately. Aggregate productivity growth in 2020 and 2021 is very similar across both sectors, with 5% for manufacturing and 6.2% for services in 2020, and 2.3% versus 2.6% in 2021. In both cases, the unweighted within-firm productivity growth is the dominant component. While the reallocation component was −1.6% for manufacturing in 2020, services saw a deterioration of −3.7%. Moreover, while reallocation turned positive again for manufacturing in 2021, this component remains negative for services.

Table 17
Decomposition of labor productivity growth.

Year	Growth agg. LP	Survivors: average	Survivors: covariance	Entry	Exit
2006	0.043	0.022	0.021	−0.006	0.006
2007	0.036	0.025	0.004	−0.004	0.011
2008	−0.004	−0.014	0.005	−0.004	0.009
2009	0.006	0.004	−0.004	−0.004	0.009
2010	0.043	0.025	0.014	0.000	0.004
2011	0.008	0.000	0.001	−0.004	0.010
2012	0.019	−0.003	0.015	−0.003	0.011
2013	0.017	0.006	0.003	−0.003	0.011
2014	0.016	0.001	0.009	−0.003	0.010
2015	0.016	0.006	0.004	−0.003	0.010
2016	0.009	0.010	0.000	−0.011	0.009
2017	0.000	−0.035	0.033	−0.003	0.005
2018	0.009	0.025	−0.022	−0.005	0.010
2019	0.012	0.020	−0.014	−0.003	0.009
2020	0.059	0.085	−0.035	−0.003	0.013
2021	0.021	0.043	−0.010	−0.005	−0.007

Table 18
Decomposition of TFP growth.

Year	Growth agg. TFP	Survivors: average	Survivors: covariance	Entry	Exit
2006	0.045	0.027	0.020	−0.006	0.005
2007	0.039	0.031	0.006	−0.008	0.011
2008	0.000	−0.009	0.006	−0.005	0.008
2009	0.015	0.005	0.004	−0.005	0.010
2010	0.052	0.030	0.019	−0.003	0.006
2011	0.007	0.007	−0.007	−0.005	0.012
2012	0.021	0.002	0.016	−0.005	0.008
2013	0.022	0.010	0.007	−0.004	0.009
2014	0.022	0.008	0.007	−0.004	0.011
2015	0.023	0.011	0.005	−0.003	0.010
2016	0.020	0.017	−0.002	−0.004	0.008
2017	0.008	−0.023	0.029	−0.003	0.005
2018	0.014	0.029	−0.021	−0.005	0.011
2019	0.036	0.024	−0.004	0.008	0.008
2020	0.042	0.047	−0.007	−0.005	0.007
2021	0.060	0.058	−0.009	0.012	−0.001

Table 19
Decomposition of labor productivity growth, manufacturing (NACE 10-33).

Year	Growth agg. TFP	Survivors: average	Survivors: covariance	Entry	Exit
2006	0.057	0.030	0.025	−0.004	0.006
2007	0.022	0.035	−0.020	−0.004	0.011
2008	−0.024	−0.014	−0.013	−0.002	0.005
2009	0.020	−0.011	0.022	0.000	0.010
2010	0.070	0.027	0.033	0.002	0.008
2011	0.009	0.009	−0.006	−0.002	0.008
2012	0.022	−0.001	0.013	0.000	0.010
2013	0.031	0.007	0.014	0.000	0.010
2014	0.044	0.023	0.013	−0.001	0.009
2015	0.027	0.012	0.006	0.000	0.008
2016	0.034	0.016	0.016	−0.006	0.008
2017	0.006	−0.014	0.018	−0.002	0.004
2018	0.000	0.018	−0.021	−0.002	0.006
2019	0.009	0.013	−0.008	−0.002	0.006
2020	0.050	0.063	−0.016	−0.002	0.006
2021	0.023	0.045	0.012	−0.003	−0.031

Appendix F. Multi-group decomposition

This section provides the derivation of the decomposition with the group of treated the group of untreated firms from the standard Olley and Pakes (1996) and Melitz and Polanec (2015) decompositions (further referred to as OP and MP). The MP decomposition distinguishes three groups of firms: survivors, entrants and exiting firms. Aggregate productivity growth is defined

Table 20
Decomposition of labor productivity growth, services (NACE 35-82).

Year	Growth agg. TFP	Survivors: average	Survivors: covariance	Entry	Exit
2006	0.039	0.020	0.018	−0.005	0.006
2007	0.048	0.025	0.015	−0.003	0.011
2008	0.009	−0.013	0.016	−0.004	0.010
2009	0.004	0.007	−0.007	−0.004	0.008
2010	0.031	0.024	0.006	−0.001	0.001
2011	0.010	0.001	0.002	−0.004	0.011
2012	0.019	−0.005	0.017	−0.004	0.011
2013	0.013	0.007	0.000	−0.004	0.011
2014	0.007	−0.002	0.003	−0.003	0.010
2015	0.013	0.004	0.003	−0.004	0.010
2016	0.002	0.009	−0.006	−0.010	0.009
2017	−0.001	−0.038	0.034	−0.002	0.005
2018	0.014	0.027	−0.019	−0.004	0.011
2019	0.016	0.020	−0.012	−0.001	0.009
2020	0.062	0.088	−0.037	−0.002	0.013
2021	0.026	0.043	−0.018	−0.002	0.003

in Section 4 as the evolution in weighted average of firm-level log productivity and can be written as:

$$\triangle \Phi_t = \underbrace{\Phi_2^S - \Phi_1^S}_{\text{survivors}} + \underbrace{s_2^E \left(\Phi_2^E - \Phi_2^S\right)}_{\text{entrants}} + \underbrace{s_1^X \left(\Phi_1^S - \Phi_1^X\right)}_{\text{exiters}}$$

For the multi-group decomposition, we focus on the first term of surviving firms. Employment in FTE is used for the weights s_{it} to aggregate up firm-level log productivity φ_{it} to aggregate productivityΦ_t, while s_t^g denotes the total market share of a group $g \in \{T, NT\}$ at time $t = 1, 2$. Aggregate productivity growth can thus be described as

$$\begin{aligned} \triangle \Phi_t^S &= \Phi_2^S - \Phi_1^S \\ &= s_2^{S,T}\Phi_2^{S,T} + s_2^{S,U}\Phi_2^{S,U} - s_1^{S,T}\Phi_1^{S,T} - s_1^{S,U}\Phi_1^{S,U} \end{aligned} \tag{4}$$

The issue with the equation above is that changing market shares will show up in both the aggregate productivity term Φ_t and the group market share $s_t^{S,g}$. For the division along the treatment dimension, a second weight is therefore used, namely the number of firms in each group $n_t^{S,g}$. Note that firms are only treated in 2020, so the number of firms that are treated and the number of firms that are untreated remain constant among surviving firms over both 2020 and 2021, so $n_1^{S,g} = n_2^{S,g} = n^{S,g}$. Yet, market shares $s_t^{S,g}$ might change from one year to the next.

To develop the multi-group decomposition, we expand Eq. (4) with additional terms in lines 2–4 that just cancel out against each other:

$$\begin{aligned} \triangle \Phi_t^S = {} & s_2^{S,T}\Phi_2^{S,T} + s_2^{S,U}\Phi_2^{S,U} - s_1^{S,T}\Phi_1^{S,T} - s_1^{S,U}\Phi_1^{S,U} \\ & + (n^{S,T}\Phi_2^S + n^{S,U}\Phi_2^S) - (s_2^{S,T}\Phi_2^S + s_2^{S,U}\Phi_2^S) \\ & + n^{S,T}\Phi_2^{S,T} - n^{S,T}\Phi_2^{S,T} + n^{S,U}\Phi_2^{S,U} - n^{S,U}\Phi_2^{S,U} \\ & - [(n^{S,T}\Phi_1^S + n^{S,U}\Phi_1^S) - (s_1^{S,T}\Phi_1^S + s_1^{S,U}\Phi_1^S)] \\ & - [n^{S,T}\Phi_1^{S,T} - n^{S,T}\Phi_1^{S,T} + n^{S,U}\Phi_1^{S,U} - n^{S,U}\Phi_1^{S,U}] \end{aligned}$$

The terms can then be grouped together to form a term for the treated group T, a term for the untreated group NT, and a between-group covariance term as follows:

$$\begin{aligned} \triangle \Phi_t^S = {} & n^{S,T}(\Phi_2^{S,T} - \Phi_1^{S,T}) + n^{S,U}(\Phi_2^{S,U} - \Phi_1^{S,U}) \\ & + (s_2^{S,T} - n_2^{S,T})(\Phi_2^{S,T} - \Phi_2^S) + (s_2^{S,U} - n_2^{S,U})(\Phi_2^{S,U} - \Phi_2^S) \\ & - [(s_1^{S,T} - n_1^{S,T})(\Phi_1^{S,T} - \Phi_1^S) + (s_1^{S,U} - n_1^{S,U})(\Phi_1^{S,U} - \Phi_1^S)] \end{aligned}$$

where the first line of the equation entails the term for the treated group and the untreated group and the second and third line the evolution in the between-group covariance. The terms for the treated and the untreated group can then be decomposed using the OP decomposition into a within-firm evolution and covariance term:

$$\begin{aligned} \triangle \Phi_t^S = {} & n^{S,T}[\triangle \bar{\varphi}_t^{S,T} + \triangle \sum_{i \in T} \left(s_{it}^S - \bar{s}_t^{S,T}\right)\left(\varphi_{it}^S - \bar{\varphi}_t^{S,T}\right)] \\ & + n^{S,U}[\triangle \bar{\varphi}_t^{S,U} + \triangle \sum_{i \in NT} \left(s_{it}^S - \bar{s}_t^{S,U}\right)\left(\varphi_{it}^S - \bar{\varphi}_t^{S,U}\right)] \\ & + (s_2^{S,T} - n^{S,T})(\Phi_2^{S,T} - \Phi_2^S) + (s_2^{S,U} - n^{S,U})(\Phi_2^{S,U} - \Phi_2^S) \\ & - [(s_1^{S,T} - n^{S,T})(\Phi_1^{S,T} - \Phi_1^S) + (s_1^{S,U} - n^{S,U})(\Phi_1^{S,U} - \Phi_1^S)] \end{aligned}$$

Finally, the multi-group decomposition for surviving firms from the two groups g of treated and untreated can be summarized as:

$$\triangle \Phi_t^S = \underbrace{\sum_{g=1}^{2} n^{S,g} \left(\Delta \bar{\varphi}_t^{S,g}\right)}_{\text{within-firm growth}} + \underbrace{\sum_{g=1}^{2} n^{S,g} \left(\Delta Cov\left(s_t^{S,g}, \varphi_t^{S,g}\right)\right)}_{\text{intra-group covariance change}} + \underbrace{\Delta Cov_{inter,t}^{S,g}}_{\text{inter-group covariance change}}$$

Appendix G. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.euroecorev.2023.104508.

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