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Abstract

We analyze the impact of Covid-19 rescue policies on both firm-level and aggregate productivity growth and reallocation. Using administrative data on the universe of firms' subsidies in Flanders, we estimate the causal impact of these subsidies on firm-level outcomes. Firms that received subsidies saw a 7% increase in productivity, compared to firms that applied for, but did not obtain subsidies. Furthermore, the propensity to exit the market was 43% lower for treated firms. Aggregate productivity growth, a share-weighted sum of firms' productivity evolutions, amounted to 6% in 2020. While within-firm productivity growth was similar for both subsidized and non-subsidized firms, there is a reallocation of market shares from subsidized firms to non-subsidized firms. These results suggest that Covid rescue policies helped firms to sustain and preserve productivity, while not obstructing allocative efficiency gains to non-subsidized firms.

JEL Codes: D22 , D24 , O4.

Keywords: Productivity, productivity growth, aggregate productivity, allocative efficiency.

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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 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, it has been argued that government intervention 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 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 these firm subsidies in detail. In particular, we focus on the following questions: (i) "what is the impact of the Covid-19 subsidies on firm-level outcomes?", and (ii) "how do these subsidies affect aggregate productivity growth and allocative efficiency?".

To answer these questions, we first combine four administrative datasets for the universe of firms in Flanders (Belgium).[1] We use data on all Flemish companies applying for a Covid subsidy in 2020. This data contains information at the firm-application level, with the date of application, whether the subsidy was approved or not, and if granted, the date and amount of the payment. For all companies that applied, we combine this information with sales from their quarterly VAT declarations. For the universe of Flemish firms, 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 variables from the annual accounts at Bureau Van Dijk.

Next, we estimate the causal effect of these subsidies on firm-level outcomes using a difference-in-differences strategy. In particular, we compare company outcomes before and after treatment (first difference) with companies that applied for but did not obtain subsidies (second difference). Within firms over time, we find that subsidized firms increased productivity by 7-8% more, relative to similar firms that did not obtain support.

[1] In many countries, firms could apply for rescue subsidies 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 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 were able to receive confidential data on the various support measures.

Exploiting the rich panel structure, we also estimate the impact of the subsidies on quarterly growth. This setup allows to further scrutinize and confirm the parallel trends assumption, and to estimate the persistence of the impact of policy support on firm-level outcomes. We find that labor productivity increases with 5% in the first quarter of the first subsidy, and still persists with a positive and significant 3% in the second quarter after treatment.

There is significant heterogeneity in the nature of the individual subsidy types, which range from lump sum to ad valorem subsidies, and in terms of the total amount allocated to firms 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 aggregate impact of the policy.

We then estimate attrition rates for treated versus non-treated firms. Even while aggregate exit rates were very low over this period 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 43% lower probability to exit the market. In the absence of firm subsidies, aggregate firm exit would have been 8% higher.

We also provide several robustness results, 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 & Abraham (2021) to control for heterogeneous treatment effects in a pooled estimation setup. All results confirm our baseline estimates.

In the second part of the paper, we turn to the implications of firm-level support measures on aggregate productivity growth. We first decompose aggregate productivity growth into its main components, value added and labor. While both value added and employment dropped in 2020, the decline in employment was much larger than that in value added, generating a positive productivity growth of 6.1% in 2020. This positive productivity growth is robust to several alternative measures, including TFP.

We then decompose aggregate growth into four firm-level components, building on Olley & Pakes (1996) and Melitz & Polanec (2015): (i) an unweighted average growth rate of surviving firms, (ii) the change in covariance in market shares and productivity, a measure of the change in allocative efficiency, (iii) the aggregate contribution of entering firms, and (iv) the contribution of exiting firms. Aggregate productivity growth is mostly driven by the unweighted productivity of surviving firms (8.3%). However, there is a negative covariance effect (-3.5%), which might suggest attenuated creative destruction, as firms with productivity slowdowns gain market shares.

There is also a positive net entry effect (1.3%) implying that exiting firms raise aggregate productivity.

Finally, based on our findings from the difference-in-differences setup, we provide a decomposition that allows to further linearly separate these components across treated versus non-treated firms. This decomposition includes an additional reallocation term between treated and non-treated firms and its effect on aggregate productivity. We find that, within firms, both treated and untreated firms contribute to aggregate productivity growth. Their contributions in the aggregate are very similar, but since the market share of treated firms is much smaller, this suggests that treated firms contribute more on average per firm, consistent with our diff-in-diff results. These results suggest that the productivity growth was not just a catch-up effect, but in fact a higher contribution to positive productivity growth. While there is evidence of reduced allocative efficiency in both treated and untreated groups, there is a reallocation of market shares from treated to the untreated firms, suggesting a positive effect of creative destruction towards more productive, untreated firms at the level of the economy.

There are several papers that have evaluated the impact of Covid-19 on firm-level outcomes. Dhyne & 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 & 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. 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 subsidies 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.

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 from firms receiving support versus those not receiving support and we analyze whether reallocation matters for aggregate productivity growth. In Section 5, we discuss some robustness exercises. We conclude in Section 6.

2. Data and Summary Statistics

2.1 Data sources and construction

We combine four firm-level datasets to analyze the impact of Covid support measures on firm-level and aggregate productivity growth. First, we use data on all Flemish companies applying for a VLAIO Covid subsidy in 2020.[2] This dataset contains information for each application submitted by a company, with the date of application, the sector of economic activity that applies to the subsidy, whether or not the application was approved, and if granted, the date and amount of the payment. This confidential data is courtesy of VLAIO, the Flanders Innovation and Entrepreneurship Agency that administered and distributed the Covid subsidies. Second, for all companies that applied, we observe quarterly sales from 2019 up to and including the third quarter of 2020 from the VAT declarations, administered at the Federal Finance Office. Third, for the universe of Flemish companies, we obtain information on employment in terms of full-time equivalents (FTE), and the main economic activity at the NACE 5-digit level from the Social Security Office, reported quarterly from 2005 onwards. We also use this dataset to identify firm exit at the quarterly level, defined as not submitting compulsory social security statements in subsequent quarters. Finally, we extract information on input expenditures, fixed assets, sales, value added, age and debt-to-asset ratios for all companies in Flanders that submit annual accounts for the period 2005-2020 from Bureau Van Dijk.[3] Across these datasets, all companies are identified by a unique VAT number, allowing for unambiguous merging.

We retain companies across all market activities, spanning NACE Rev. 2 (2008) codes 01-82, thus including primary, secondary and tertiary sectors. We group some NACE 2-digit sectors to contain at least 250 observations, needed to estimate sectoral production functions and structural

[2] We use companies and firms interchangeably throughout. The vast majority of these support measures in fact applies to companies or entrepreneurs in very downstream sectors, services and/or incorporated independents, rather than classic manufacturing firms.

[3] Only companies above certain size thresholds have to submit annual accounts. Conditional on submission, micro and small companies can submit abbreviated annual accounts excluding sales and inputs expenditures, and large companies have to submit full accounts. See the size criteria here.

TFP.[4] See Appendix A for a list and description of these sectors. For the main analysis studying labor productivity, we restrict the data to companies that report strictly positive value added, employment and capital, to allow for comparable analysis throughout the different sections. If one of these variables is missing in one period, we interpolate its value using a simple average of $t-1$ and $t+1$.

2.2 Company-level support measures

We start by providing some context and information on the VLAIO Covid subsidies. To flank federal sanitary policies such as forced sector lockdowns, the Flemish government issued measures to support companies that were forced to close or saw a large reduction in their sales. The goal was to keep the economy afloat and to avoid liquidity issues, layoffs, and firm failures as a direct result of the sanitary policies that had been implemented. Measures were issued at the sectoral (NACE) level. For example, if a lockdown on all non-essential stores was imposed, companies that were active in these closed sectors would become eligible for the flanking support measures. Similarly, if social distancing implied that all contact professions (hairdressers, chiropractors etc.) would remain closed, these sectors would be eligible for compensation. A detailed timeline of the tandem of sanitary and support measures is given in Appendix B.

The scale and speed of this program is impressive: the online application process required only some basic information on the company (its VAT number and name, the location of the main seat, a bank account, and its related sector of activity), and the median payout rate was only two days after application. Between March 12 and Dec 31 2020, a total of 1.7 billion euros has been allocated through this channel. It is important to note that these subsidies do not count as revenues in companies' accounts, which could otherwise lead to a mechanical positive correlation in support policies and firm productivity in our following analysis.

As restrictive policies changed throughout the year, the supporting subsidies also evolved. Table 1 describes the five support measures that have been paid throughout 2020, the requirements and subsidy amount, and their coverage period. The measures can be broadly categorized along two dimensions: (i) a premium 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 subsidies (premia 4-5).[5] Figure 1 shows the number of companies supported by each type of subsidy, and the total amounts paid by premium. The first subsidy,

[4] The NACE 2-digit code of a firm is treated as fixed over time.

[5] 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 are left out of the analysis. The right tail of the first five premia is missed in an analysis of the impact in 2020. The tail only contains at most 1% of the requested payments of the first four premia and 9% of the fifth premium.

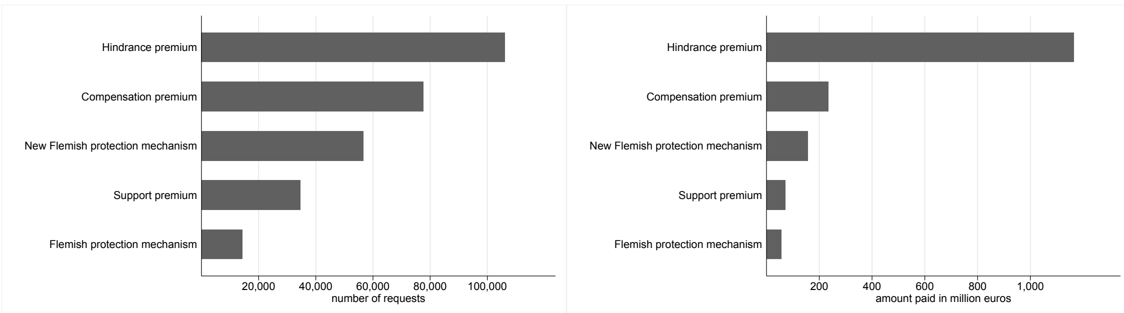
Table 1: VLAIO support measures (2020).

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

the Hindrance premium, accounts for over 50% of the total subsidy amount in 2020, supporting over 100,000 entities. This suggests that a large part of the expected impact of the overall program might be contributed to the Hindrance premium. To evaluate this, we will estimate the impact of the overall program on company outcomes within companies over time, as well as the potential differential effects of the different types of subsidies in Section 3.

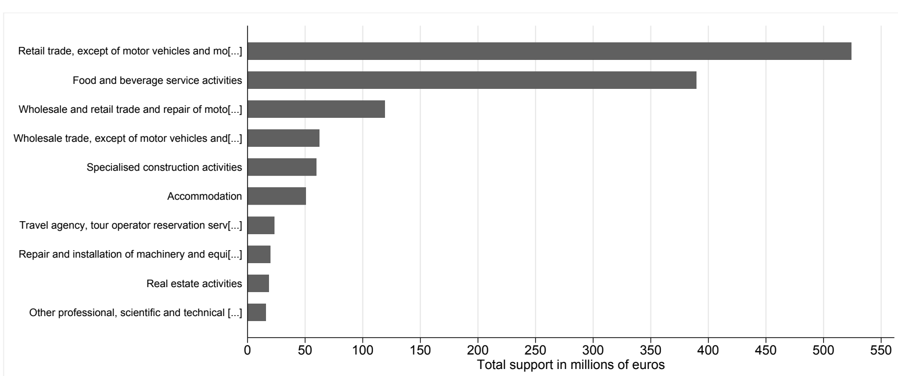
There is also significant heterogeneity across sectors in terms of support. Figure 2 shows the top 10 sectors in terms of the amount of VLAIO support received in 2020. Over 500 million euro went to retail trade, followed by the food and beverage sector with almost 400 million euro. Other sectors include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

Figure 1: VLAIO Covid support, per premium (2020).



Notes: This figure shows the total number of requests and the total amounts paid per premium in 2020.

Figure 2: Top 10 sectors, value of support (2020).



2.3 Event study dataset

To estimate the causal impact of the Covid support measures on company-level outcomes, we use the set of companies that applied for Covid support measures in 2020, and that also submit annual accounts. For these, we observe their quarterly performance from 2019q1 to 2020q3. We combine quarterly information on employment and sales from the Social Security and VAT declarations with the yearly information on value added from the annual accounts. We use a balanced panel: to be eligible for support, companies had to be active in targeted sectors in 2019. This allows us to compare within-firm performance *ex ante* and *ex post* subsidy. The final dataset contains 29,393 firms.

Firms are classified as either treated (received support) or untreated (applied for but did not receive support). Table 2 shows some summary statistics for both treated and untreated firms for the year 2019, i.e. before the Covid shock and related support measures. The median employment for both treated and untreated are comparable, at respectively 2.1 and 2.4 FTEs. However, for untreated, the distribution is more right-skewed, so that, on average, treated firms are smaller than untreated firms. For value added, the median values are 173,000 and 236,000 euro respectively; for turnover, this is 472,000 and 478,000 euro. In terms of labor productivity, median values are 74,000 euro versus 87,000 euro (value added per FTE) and 214,000 versus 186,000 (sales per FTE). These moments confirm that on average, treated firms are smaller than non-treated firms. However, as we show in Section 3, labor productivity and TFP growth rates were very similar across both groups before treatment, confirming the key identifying assumption of parallel trends in the outcome variable for the event study analysis.

2.4 Aggregate productivity growth dataset

To track aggregate growth of the Flemish economy across several years, we use the population of companies with annual accounts in Flanders from 2005 to 2020. This data differs from the first dataset in two dimensions. First, this data constitutes a relatively long unbalanced panel of companies covering the period 2005 to 2020. Second, in the cross-section, the dataset contains not only companies that applied for Covid-19 support measures, but also all other companies that did not apply for support. 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 1,305,343 firm-year observations from 164,323 unique companies from 2005 to 2020. Table 3 shows a summary of the main variables

Table 2: Summary statistics treated/untreated (2019).

				percentiles		
	Variable	Mean	Std. Dev.	p10	p50	p90
Treated	Employees (FTE)	5.9	32.4	0.5	2.1	11.4
(N = 25,682)	Value added	471,714	2,537,335	41,810	173,312	877,164
	Turnover	1,773,359	11,155,806	135,499	472,591	2,733,765
	Value added/FTE	128,484	585,146	41,370	74,290	181,898
	Turnover/FTE	560,660	2,749,013	87,535	213,744	832,550
Untreated	Employees (FTE)	12.7	174.2	2.4	2.4	14.2
(N = 3,681)	Value added	1,006,493	8,885,265	58,819	236,243	1,305,899
	Turnover	2,013,072	9,480,386	121,881	478,784	3,161,786
	Value added/FTE	150,735	449,553	48,609	86,713	227,732
	Turnover/FTE	435,798	2,712,124	75,540	185,827	686,542

Notes: This table reports the distributions of yearly variables of treated and untreated companies in 2019. Employment is expressed as the number of full-time equivalents (FTE) at the company, averaged over quarters in 2019; value added and turnover are the totals in euros over quarters in 2019. p10, p50 and p90 indicate the 10th, 50th and 90th percentiles.

Table 3: Summary statistics productivity growth, pooled (2005-2020).

			percentiles		
Variable	Mean	Std. Dev.	p10	p50	p90
Employees (FTE)	12.0	99.3	0.5	2.4	18.5
Value added	1,224,166	15,398,531	41,102	201,594	1,564,995
Value added/FTE	165,290	1,342,774	39,979	77,633	224,074
Tangible fixed assets	1,090,784	18,975,177	8,123	119,297	1,120,568

Notes: Employment is expressed as the number of full-time equivalents (FTE); value added and tangible fixed assets are in euros. All variables are yearly values, pooled over 2005-2020. p10, p50 and p90 indicate the 10th, 50th (median) and 90th percentiles.

used for analysis, pooled over all years. The median company in this dataset employs 2.4 FTE's, generates 202,000 euro of value added a year, and has 119,000 euro in capital stock. The median labor productivity is 77,000 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 Appendix D, which also uses tangible fixed assets when estimating sectoral production functions.

3. The Impact of Covid Subsidies on Firm Performance

3.1 Identification strategy

We want to estimate the causal impact of VLAIO Covid subsidies on firm productivity. To do so, we exploit data on the population of companies for the years 2019-2020 that applied for VLAIO Covid support in 2020. We estimate a simple difference-in-differences setup. In particular, we compare company outcomes before and after treatment (first difference) with companies that applied for but did not obtain subsidies (second difference).

Companies are classified as those that received a subsidy in 2020 ("treated") and those that applied, but did not get support ("untreated"). We argue that the latter is 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, or for premium 2 onwards, experienced a sales drop that was less than 60% in the reference period of 2019. In fact, potential non-random selection into treatment, e.g. companies 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 biasing downwards our estimates of the true impact of the subsidies on company 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 of the groups of treated and non-treated companies 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 evaluate pre-trends in the quarterly analysis to validate this assumption empirically. To further corroborate this assumption, we also provide a placebo test in which firms are counterfactually treated in the last quarter of 2019 and first quarter of 2020 in Section 5. 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 subsidies changed over time, the non-anticipation assumption is plausibly justified. 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. SUTVA also implies that it does not matter if there is a difference in the size of the treated or untreated group.

We first estimate a canonical difference-in-differences model of two periods (2019-2020) and two groups (treated/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 potential persistence effects in policy. Next, we estimate the quarterly model for individual premium types to evaluate potential heterogeneity in 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 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 in 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 & Abraham (2021) to control for heterogeneous treatment effects in a pooled estimation setup.

3.2 Yearly diff-in-diff

We first estimate the overall effect of the Covid subsidies on firms' productivity in 2020. Under the stated assumptions, and for two periods (years 2019 and 2020) and two groups (treated vs untreated), the ATT can be consistently estimated using a Two-Way Fixed Effects (TWFE) regression of the following form (Roth et al., 2022):

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

where we measure labor productivity Y_{it} either as log sales per FTE or log value added per FTE. $D_{it} = 1$ if company i received support in year t, and 0 otherwise. Firm fixed effects α_i control for unobservables that are constant *ex ante* and *ex post* treatment, and allow to evaluate the within-firm effect of treatment on labor productivity outcomes. Year fixed effects λ_t control for common aggregate trends, such as the massive Covid shock in 2020.

Table 4 shows the results of estimating Equation 1. Compared to non-treated firms, companies that received Covid subsidies experienced a positive and significant impact on productivity: the ATT is around 7%, irrespective of the measure of labor productivity we use. This suggests that companies that received support have been able to increase their labor productivity more *ex post* than the control group of companies that did not receive support. It is possible that all firms experienced a strong negative shock to labor productivity. To the extent that companies receiving support were also hit more by a negative shock than untreated firms, this would suggest that the overall policy helped treated companies to catch up again with others that were *ex ante* similar in terms of productivity growth. We return to this interpretation 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. In particular, companies could have received support in the second and/or third

Table 4: Impact of subsidies on productivity, annual.

	ln(sales/FTE)	ln(value added/FTE)
Treatment D_{it}	.078***	.070***
	(.014)	(.016)
Year fixed effects	Yes	Yes
Firm fixed effects	Yes	Yes
Adj. R^2	0.82	0.59
N	58,726	58,726

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

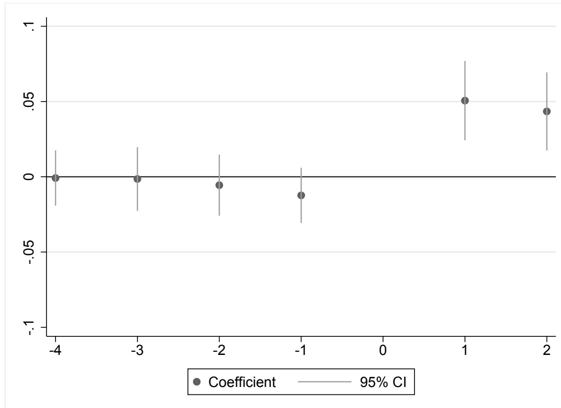
quarter of 2020. We thus have a staggered treatment model, with some companies receiving support for the first time in the second quarter, others only in the third quarter, and others receiving no support at all. Following the literature (Roth et al., 2022), we consider companies to be treated from the first quarter they receive support. We estimate the following TWFE model:

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

We measure Y_{it} only as log sales per FTE as we have no quarterly information on value added per FTE. The treatment dummies D_{ik} indicate whether the company got the first subsidy 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 $(k = -4, ..., -1)$ and a post-treatment period $(k = 1, 2)$. This setting allows for heterogeneous treatment effects *over time*. Heterogeneous treatment effects *across firms* are further explored in the next section and in Section 5. We additionally control for firm fixed effects α_i, and industry-quarter effects λ_{jt}, where j indexes the industry of company i. Coefficients are normalized to zero in $k = 0$, the quarter before a company received support.

Figure 3 plots the coefficients from estimating Equation 2 for all quarters k, together with 95% confidence intervals. Some notes. First, point estimates for the 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 5% in the first quarter post treatment, and around 3% in the following quarter, both sta-

Figure 3: Impact of subsidies 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.

tistically different from zero at the 5% significance level. This suggests that the policy generated significant and persistent effects in productivity growth after intervention.

3.4 Diff-in-diff by premium

Next, it is possible that the different subsidies have a differential effect on firm performance. First, there is sizable variation in the amounts allocated through each subsidy type, and premium 1 was by far the largest subsidy in terms of both number of applications and allocated funding. Second, subsidies varied in their requirements and support: forced closure (premium 1) vs a significant drop in turnover (premia 2-5), and flat fees (premia 1-3) vs ad valorem fees (premia 4-5). To elaborate on these distinctions, the subsidies are divided into three groups; the hindrance premium (premium 1), the compensation and support premium (premia 2 and 3) and finally, the Flemish protection mechanism and new Flemish protection mechanism (premia 4 and 5).

Table 5 shows the yearly results when regressing labor productivity on a treatment dummy and dummies for each group of premia. Value added per FTE is used as the measure for labor productivity as it is reported in the annual accounts for the whole of 2020. A firm can be supported through multiple premia, so the treatment dummy is not perfectly collinear with the other three dummy variables. The treatment dummy coefficient captures the average treatment effect across all types of premia. The estimates by premia reflect the differential treatment effect of each premium relative to the average across premia. The total effect of a particular premium is then the sum of the treatment coefficient and the corresponding dummy coefficient.

Table 5: Difference-in-differences by subsidy separately, annual.

	ln(value added/FTE)
Treatment D_{it}	.097**
	(.034)
Premium 1	.030
	(.031)
Premium 2 or 3	-.086**
	(.029)
Premium 4 or 5	-.055***
	(.014)
Year fixed effects	Yes
Firm fixed effects	Yes
Adj. R^2	0.59
N	58,726

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

The first premium constitutes the bulk of total value and number of companies supported, so it will 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. Especially for small firms, the impact can be large, evidenced by the positive coefficient. Indeed, the point estimate for the average treatment effect of premium one is 13%, and insignificantly different from the overall treatment coefficient estimated at 9.7%. The second and third premium 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 1%, but not significantly different from zero. The final premia four and five take a different approach where the value of the support is calculated as a percentage of turnover. The average treatment effect for firms that got ad valorem fees is smaller than for the first premium, but still larger than the second and third premia at 4%.

These results suggest that the effect of the support policies in 2020 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, at the beginning of the crisis.

3.5 Propensity to exit

We conclude this section by studying the impact of subsidies on firm exit. One of the key rationales for the VLAIO support was to avoid firm exit as a direct consequence of the sanitary policies. During most of 2020, 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 was at the lowest rate in 13 years. Firms could still be liquidated voluntarily though, e.g. when in liquidity or capital constraints, so firm exit was still positive, albeit much lower than in normal times.

We therefore analyze how the Covid subsidies affected firm exit. The control group now also includes all companies that did not request support, to enlarge the set of potentially exiting firms.[6] We also provide 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 companies with less debt are generally known to have lower exit rates. Conditional on these controls, the estimated impact of support on exit is substantial: the marginal effect of retrieving support is a decline in the average exit probability of 0.6 percentage points, and this coefficient is stable across specifications.

To interpret this result, Table 7 shows the decomposition of predicted exit probabilities from the logit model. The unconditional average exit probability is 1.3% in any quarter of 2020. This implies that the 0.6 p.p. drop relates to a decline of 43% in exit probabilities. The counterfactual exit probability in case of no support would have been 1.4%, or an 8% increase in the incidence of exit. Conversely, in a scenario in which all firms would have received support, the counterfactual exit probability is 0.8%. The decomposition also shows that supported companies would especially be worse off in the absence of the support scheme. The logit estimates imply that the average exit probability for the group of supported companies would have risen from 1.3% to 2.1%.

These results show that subsidized companies 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.

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

Table 6: Probability of exit, quarterly.

	Pr(exit)	Pr(exit)	Pr(exit)
Treatment D_{it}	-0.600***	-0.604***	-0.607***
	(0.133)	(0.133)	(0.134)
ln(value added/FTE)	-0.380***	-0.377***	-0.374***
	(0.031)	(0.031)	(0.031)
ln(FTE)	-1.130***	-1.126***	-1.121***
	(0.052)	(0.052)	(0.052)
debt/asset ratio 2019		0.065**	0.056**
		(0.025)	(0.027)
ln(age)			-0.140***
			(0.047)
Unconditional exit probability		1.3%	
Quarter fixed effects	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes
Pseudo R^2	0.193	0.194	0.194
N	145,647	145,647	145,647

Notes: Exit is a dummy variable which indicates whether a company 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	1.3%
Counterfactuals	
1. If no firms had received support	1.4%
2. If firms that did get support had not received support	2.1%
3. If all firms had received support	0.8%
4. If firms that did not get support had received support	0.7%

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

4. Aggregate Productivity Growth, Covid Support and Reallocation

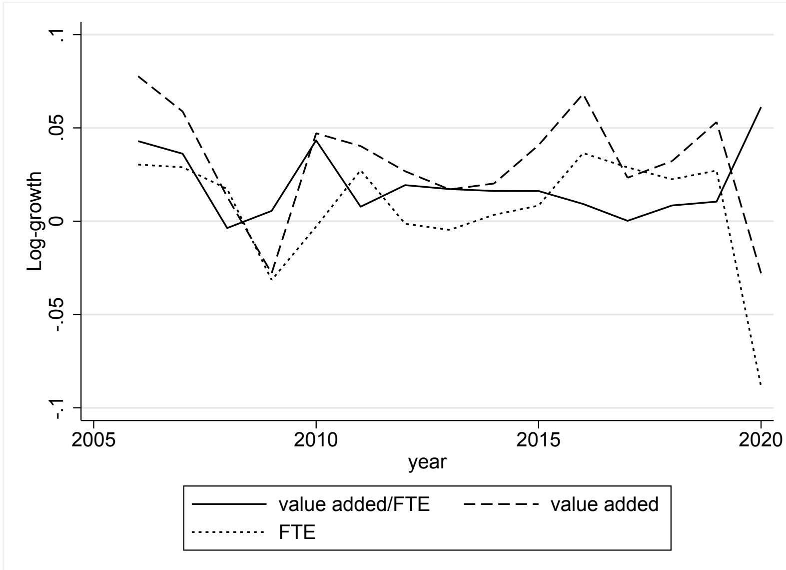
In this section, we analyze firm-level contributions to aggregate productivity growth. We first decompose aggregate productivity growth into its main components, value added and labor. We then develop a decomposition of aggregate growth into various firm-level components, based on the findings from the difference-in-differences setup in Section 3. This decomposition builds on Olley & Pakes (1996) and Melitz & Polanec (2015), to include a reallocation effect between treated and non-treated firms and its effect on aggregate productivity.

4.1 Aggregate productivity growth and its main components

We start by tracking aggregate productivity growth over the period 2005 to 2020. Figure 4 shows the yearly evolution of labor productivity. Aggregate productivity growth is expressed as the weighted sum of value added/FTE over all firms, with firms' weights given by FTE shares. The figure also shows the growth rates of the separate components, value added and FTE. Perhaps surprising *prima facie*, productivity growth was positive during the pandemic, clocking in at 6.1%.[7] One explanation is a composition effect: both aggregate value added and FTE drop

[7] One caveat to the aggregate productivity analysis using firm-level log productivity, is the requirement for strictly positive value added. To see if this has a large impact, we calculate aggregate productivity as the total sum of value added over the total sum of FTE employment while retaining negative value added observations in Appendix C. Aggregate productivity growth in 2020 is then still 5.4%. The aggregate productivity evolution is also influenced by the choice of

Figure 4: Aggregate evolution of labour productivity, value added and employment (2005-2020).



Notes: Yearly growth rates are expressed in log-differences.

drastically in 2020. However, the drop in FTE employment (9%) was much larger than the drop in value added (3%), generating an increase in value added per FTE. We do not think however, that these productivity gains are structural or an equilibrium outcome. Perhaps output could increase with less people per unit in 2020, but the work environment was insecure, particularly for workers with temporary contracts, women and mothers, while the rate of burnout skyrocketed in 2020 (Abramson (2022)).

Moreover, this positive productivity effect is not common across crises: during the financial crisis, aggregate productivity growth was -0.4% in 2008 and 0.6% in 2009. There are a number of reasons why we might find a large and positive aggregate productivity growth in the Covid crisis and not in the financial crisis. First, furlough schemes existed in both crises, but were more generally spread and lasted much longer during the pandemic than during the financial crisis. Second, firms which were hit very hard due to the lockdown were supported by direct subsidies, which allowed them to survive and keep productivity levels high as shown in Section 3.

market shares as weights, namely FTE employment. An additional exercise considers the evolution using value added as weights, resulting in an aggregate productivity growth in 2020 of 3.7%. In every specification, productivity growth turns out to be positive in 2020.

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.[8] Aggregate productivity can be split into an unweighted average of firm productivity and a covariance term (Olley & Pakes (1996)):

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

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. A positive covariance term implies that more productive firms have higher market shares (an increase in 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.

Next, Melitz & Polanec (2015) provide a decomposition of aggregate log productivity growth, $\Delta\Phi_t$:

$$\begin{aligned} \triangle\Phi_t &= \triangle\bar{\varphi}_t + \triangle \sum_{i \in N_t} (s_{it} - \bar{s}_t)(\varphi_{it} - \bar{\varphi}_t) \\ &= \triangle\bar{\varphi}_t + \triangle Cov(s_{it}, \varphi_{it}) \\ &= \underbrace{\triangle\bar{\varphi}_t^S + \left(Cov(s_2^S, \varphi_2^S) - Cov(s_1^S, \varphi_1^S)\right)}_{\text{survivors}} + \underbrace{s_2^E \left(\Phi_2^E - \Phi_2^S\right)}_{\text{entrants}} + \underbrace{s_1^X \left(\Phi_1^S - \Phi_1^X\right)}_{\text{exiters}} \end{aligned}$$

In this formulation, aggregate productivity growth can be decomposed into four components. First, aggregate productivity increases in the within-firm unweighted average productivity growth

[8] The intuition for labor productivity growth easily carries over to TFP. Technically, TFP is $\ln(\text{value added}/\text{FTE})^{\beta_l} + \ln(\text{total fixed assets})^{\beta_k}$. When 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.

of survivors. Second, it increases when the covariance term of survivors increases. This can happen in two ways, if more market shares go to higher productive firms, or if larger firms become more productive. Third, the aggregate productivity contribution of entrants can be higher than that of survivors in period 2. Finally, the aggregate productivity component of exiting firms can be lower compared to survivors in period 1.

Table 8 shows the results of this growth decomposition for the years 2006 to 2020. Some notes. First, aggregate productivity growth is positive and large (6.1%) in 2020. Yearly growth rates are the same as in Figure 4. Second, the largest contribution comes from within-firm productivity growth of survivors. This effect is particularly strong compared to the other years. Third, the covariance term is negative in 2020. This means that less productive firms in fact gained market shares, or that smaller firms became more productive. 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 & Vanormelingen, 2022). This might imply that subsidies in fact hindered allocative efficiency, by supporting too small and/or too unproductive firms during the Covid crisis. We further explore this hypothesis below. Fourth, the net entry effect (entry + exit) contributes positively to aggregate productivity growth. This is in line with the results on firm exit in Table 6, as within sectors, less productive firms have a higher propensity to exit.

4.3 Decomposition across treated and untreated

We next provide a decomposition that allows to further linearly decompose these components across multiple subgroups. In the current application, these are the groups of treated versus non-treated firms. This decomposition generates the above components, now by subgroup, and also generates 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 subsidies on allocative efficiency.

There are $g = 1, ..., G$ subgroups or partitions. In our case, there are two subgroups: treated and untreated. Aggregate productivity of g is then denoted as

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

where $s_{gt} = \sum_{i \in g} s_{it}$ is the total market share of subgroup g. Denote s_{gt}^S to be 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. Aggregate productivity growth of surviving

Table 8: Decomposition of productivity growth.

year	Growth Agg. LP	Survivors: Average	Survivors: Covariance	Entry	Exit
2006	0.043	0.021	0.021	-0.005	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	0.005	-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	0.004	-0.003	0.011
2014	0.016	0.001	0.009	-0.003	0.009
2015	0.016	0.006	0.003	-0.003	0.010
2016	0.009	0.010	0.001	-0.011	0.009
2017	0.000	-0.035	0.033	-0.003	0.005
2018	0.008	0.025	-0.022	-0.005	0.010
2019	0.011	0.020	-0.014	-0.004	0.009
2020	0.061	0.083	-0.035	-0.003	0.016

firms is then

$$\triangle\varphi_t^S = \sum_{g=1}^{2} s_{gt}^S \Delta\bar{\varphi}_{gt}^S$$

In particular, it is the weighted sum of within-group growth of surviving firms, with weights given by the subgroup market shares of treated and non-treated firms. The covariance term now has two different elements: an intra-group change in covariance and an inter-group change:

$$\triangle cov^S = \underbrace{\sum_{g=1}^{2} s_{gt}^S \left(Cov\left(s_{g2}^S, \varphi_{g2}^S\right) - Cov\left(s_{g1}^S, \varphi_{g1}^S\right)\right)}_{\text{intra-group}} + \underbrace{\left(Cov_{inter,2}^S - Cov_{inter,1}^S\right)}_{\text{inter-group}}$$

The change in intra-group covariance is defined as before, but now by subgroup. It measures the contribution of shifts in the relation market share and productivity within a group. The new inter-group covariance measures the shift in market share and productivity in the comparison between groups, and is defined as

$$Cov^{S}_{inter,t} = \sum_{g=1}^{2} (s^{S}_{gt} - s^{S}_{t})(\bar{\varphi}^{S}_{gt} - \varphi^{S}_{t})$$

The change in inter-industry covariance for survivors is positive when group market shares shift in line with group-level aggregate productivities.

Table 9 shows these results. We focus on the evolution of surviving firms. Within-group productivity growth of both groups is fairly similar at around 4%. Given that the market share of treated firms is much smaller, this suggests 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 in fact a higher contribution to positive productivity growth. When we look at the covariance terms for both groups, we see that both are negative, but that of the treated is twice as large compared to the non-treated. This suggests that, within both groups, allocative efficiency is hindered during the Covid pandemic, but this effect is stronger in the treated group. This might point to insufficient creative destruction within the treated group, an unintended effect on competition induced by the policy. However, when we turn to the between-group reallocation effect in the last column, we see that the covariance term is positive. This means that there is a reallocation of market shares from treated to the untreated firms, suggesting a positive effect of creative destruction towards more productive, untreated firms at the level of the economy.

5. Robustness

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

5.1 Placebo test with fake treatment

To evaluate the credibility of our event study results, we conduct a placebo study where treatment is assumed to have happened two periods earlier. The support that was handed out in the second quarter of 2020 is reassigned to the last quarter of 2019 and the support of the third quarter of 2020 to the first quarter of 2020. The results of the placebo study are shown in Figure 5. Two pre-periods are lost due to the shifted treatments, while the post-periods now entail two periods 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

Table 9: Treated/Untreated Decomposition Labor Productivity Weighted by FTE

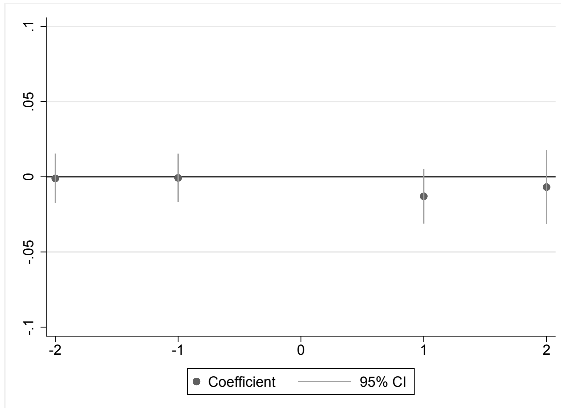
year	Gr. Agg. LP Surv.	Treated: Av.	Treated: Cov.	Untreated: Av.	Untreated: Cov.	Between Groups Cov.
2006	0.042	0.005	0.005	0.017	0.016	0.000
2007	0.029	0.006	0.003	0.020	0.002	-0.001
2008	-0.009	-0.001	0.003	-0.013	0.004	-0.002
2009	0.000	0.006	0.000	-0.001	-0.001	-0.003
2010	0.039	0.008	0.001	0.017	0.013	0.000
2011	0.001	0.001	-0.001	-0.001	0.002	-0.001
2012	0.012	0.001	0.001	-0.004	0.013	0.001
2013	0.010	0.003	0.000	0.002	0.004	-0.001
2014	0.010	0.002	0.001	-0.001	0.009	0.000
2015	0.010	0.004	-0.001	0.003	0.005	0.000
2016	0.011	0.001	-0.003	0.009	0.001	0.002
2017	-0.002	-0.013	0.009	-0.023	0.023	0.002
2018	0.003	0.009	-0.008	0.016	-0.014	0.000
2019	0.005	0.004	-0.002	0.016	-0.012	0.000
2020	0.048	0.040	-0.031	0.043	-0.016	0.011

the support and not a potential structural discrepancy between treatment and control group.

5.2 Furlough schemes

While the Flemish government installed the subsidy scheme that is the subject of this paper, the Belgian federal government implemented a furlough scheme for the Covid-19 crisis. As in many countries worldwide, the furlough scheme made it possible for firms to put employees on temporary unemployment, without ending the employment contract. In Belgium in particular, the system was already in place for certain exceptional situations, and from March 2020 onwards, the mechanism could be used on the grounds of the impact of the Covid-19 crisis. The furlough scheme allowed employees to retain 70% of their average wage for the duration of unemployment, paid by the social security system rather than the firm itself. 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 & Venn, 2011), the take-up was thus still higher in 2020. For an analysis of the impact of the furlough scheme in the financial crisis, see (Van den bosch & Vanormelingen, 2022).

Figure 5: Placebo test, quarterly diff-in-diff.



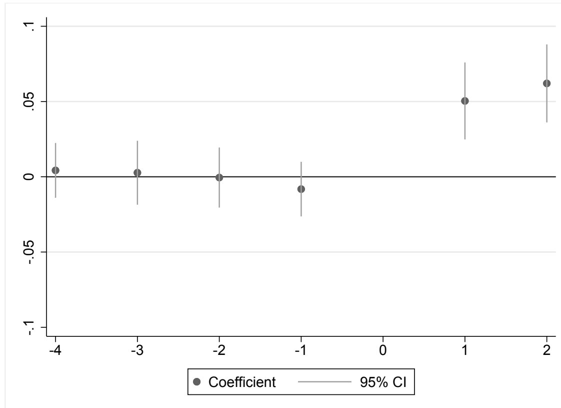
Notes: This figure shows the event study coefficients for the impact of support on labour productivity when treatment is brought forward two periods as a placebo test. Both firm fixed effects and industry-quarter fixed effects are included. Heteroscedastic robust standard errors are clustered at the firm level.

In the context of the subsidy scheme, we argued that the firms in our treatment group and in our control group both could benefit from the furlough scheme, such that the effect we pick up can be attributed to the Covid subsidy. To further support this statement, we control for the furlough scheme in the impact study analysis and show that the results hardly change. 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 in the quarterly event study. The results of this regression are shown in Figure 6. Although the point estimate for period 2 lies somewhat higher than in the baseline results, the coefficients reveal no significant differences.

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 didn't get it. In particular, we match one-on-one using the Mahalanobis distance function as a scale-invariant distance metric. We perform the 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 important units in the control group. 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 neighbours and show the results in Figure 7. Again, the

Figure 6: Impact of Support on labor productivity, quarterly diff-in-diff.

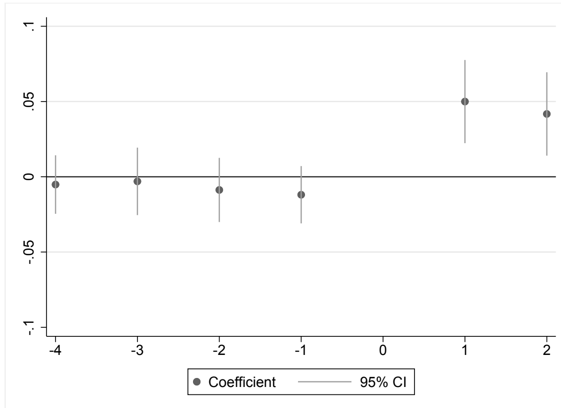


Notes: This figure shows the event study coefficients for the impact of support on labour productivity when controlling for the furlough scheme. Both firm fixed effects and industry-quarter fixed effects are included. Heteroscedastic robust standard errors are clustered at the firm level.

coefficients remain very similar to the baseline results, suggesting that the composition of the treatment and control group have no impact on our findings.

A second robustness exercise using alternative control groups concerns the analysis of the impact of support on the propensity to exit. In subsection 3.5, we included 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 10 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 0.5 percentage points, compared to the marginal effect of 0.6 p.p. found before.

Figure 7: Nearest neighbor matching results, quarterly diff-in-diff.



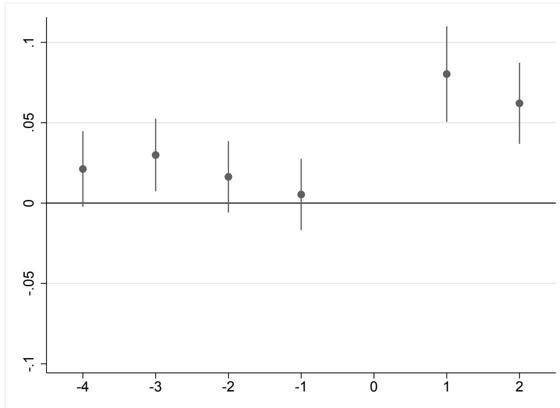
Notes: This figure shows the event study coefficients for the impact of support on labour productivity with a matched sample as control group. Both firm fixed effects and industry-quarter fixed effects are included. Heteroscedastic robust standard errors are clustered at the firm level.

Table 10: Probability of exit, quarterly.

	Pr(exit)	Pr(exit)	Pr(exit)
Treatment D_{it}	-0.372**	-0.376**	-0.369**
	(0.166)	(0.166)	(0.162)
ln(value added/FTE)	-0.424***	-0.420***	-0.406***
	(0.0327)	(0.0330)	(0.0330)
ln(FTE)	-1.135***	-1.131***	-1.115***
	(0.0482)	(0.0484)	(0.0499)
debt/asset ratio 2019		0.0657	0.0483
		(0.0666)	(0.0724)
ln(age)			-0.316***
			(0.0574)
Quarter fixed effects	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes
Pseudo R^2	0.206	0.206	0.212
N	34,128	34,128	34,128

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

Figure 8: Impact of Support on LP



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

5.4 Alternative estimator

In Section 3 we analyzed the impact of the Covid subsidies 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 subsidies. 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 a subsidy for the first time in the same quarter. We implement the estimation procedure of (Sun & 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 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. Figure 8 shows the results. While one pre-period becomes borderline significant, the overall picture remains fairly similar to the results in the main text. The coefficients for period 1 and 2 are even somewhat higher, although none of the coefficients are significantly different from the baseline analysis.

5.5 Aggregate productivity growth with structural TFP

Table 11 shows the results of the Melitz & 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 firm-level TFP using employment weights. In 2020 aggregate TFP growth is 4.5%, which is a bit lower than the 6.1% 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 in the financial crisis. Within-firm productivity growth in 2020 was highly positive, while the covariance term was negative, although it is somewhat smaller than in the labor productivity case. Furthermore, the net entry effect contributed positively to the aggregate TFP growth in 2020, similar to what we found using labor productivity.

The aggregate productivity growth of surviving firms is further decomposed in groups of treated and untreated firms in Table 12. All terms have the same signs as before. Within-firm productivity increased more for untreated firms, but there was a positive growth in both groups. In addition, reallocation is hindered in both groups. The between group allocation effect is slightly larger in terms of TFP, indicating a positive reallocation effect from treated firms to untreated firms.

5.6 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 & Haltiwanger (1992). The growth rate in employment n is then defined as:

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

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

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

Table 11: Decomposition Value Added TFP Weighted by FTE

year	Growth Agg. TFP	Survivors: Average	Survivors: Covariance	Entry	Exit
2006	0.045	0.026	0.020	-0.006	0.005
2007	0.040	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	0.054	0.030	0.019	-0.004	0.009
2011	0.005	0.008	-0.009	-0.005	0.011
2012	0.021	0.001	0.016	-0.005	0.008
2013	0.022	0.010	0.007	-0.003	0.009
2014	0.022	0.008	0.007	-0.004	0.011
2015	0.023	0.012	0.004	-0.003	0.010
2016	0.020	0.016	-0.001	-0.004	0.008
2017	0.009	-0.023	0.030	-0.003	0.005
2018	0.014	0.028	-0.020	-0.005	0.011
2019	0.034	0.023	-0.004	0.007	0.009
2020	0.045	0.046	-0.008	-0.005	0.012

Table 12: Treated/Untreated Decomposition Value Added TFP Weighted by FTE

year	Gr. Agg. TFP Surv.	Treated: Av.	Treated: Cov.	Untreated: Av.	Untreated: Cov.	Between Groups Cov.
2006	0.046	0.007	0.003	0.020	0.017	0.000
2007	0.037	0.007	0.002	0.023	0.005	-0.001
2008	-0.002	0.000	0.001	-0.009	0.007	-0.001
2009	0.010	0.006	-0.001	-0.001	0.007	-0.002
2010	0.049	0.010	0.002	0.019	0.017	0.000
2011	-0.001	0.004	-0.002	0.003	-0.005	-0.001
2012	0.017	0.002	0.001	0.000	0.014	0.001
2013	0.017	0.005	0.001	0.005	0.007	-0.001
2014	0.015	0.004	0.000	0.003	0.007	0.000
2015	0.016	0.006	0.000	0.006	0.005	-0.001
2016	0.015	0.005	0.001	0.012	-0.001	-0.001
2017	0.006	-0.008	0.009	-0.015	0.020	0.001
2018	0.008	0.010	-0.005	0.018	-0.014	-0.001
2019	0.019	0.006	0.006	0.017	-0.007	-0.003
2020	0.038	0.008	-0.012	0.037	-0.011	0.015

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). Figure 9 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. Overall aggregate employment growth was -5% in 2009, but -11% in 2020. We find a similar picture when we look at value added creation and destruction, with more value added reallocation in the pandemic (Figure 10). There has thus been a lot of reallocation in 2020, 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.

Figure 9: Gross Job Reallocation

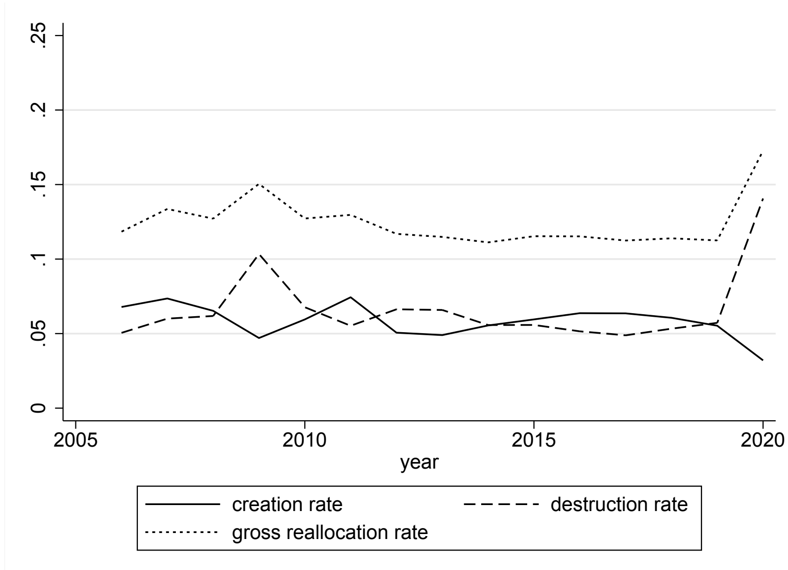
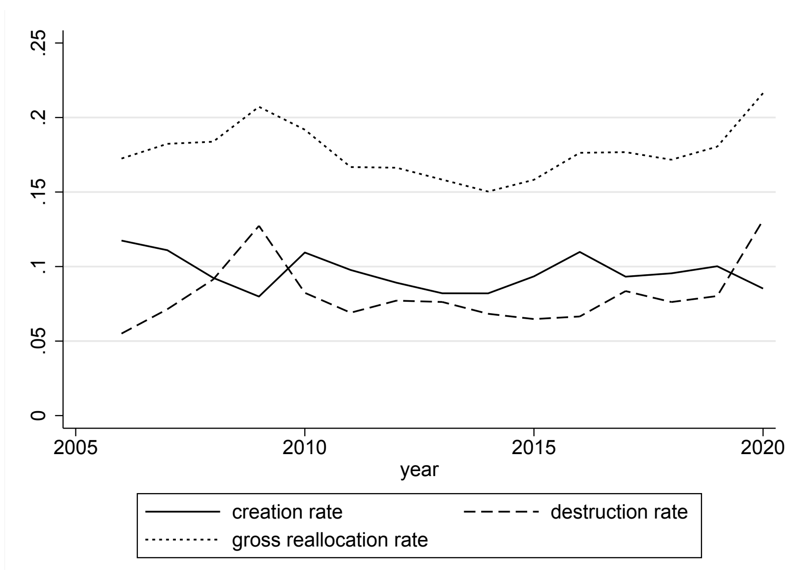


Figure 10: Gross Value Added Reallocation



6. Conclusion

In this paper, we have studied the impact of firm-level Covid-19 subsidies on firm and aggregate outcomes. Combining administrative data on the universe of firms' subsidies in Flanders with information on firm-level outcomes, we estimate the causal impact of these support measures on firm productivity. Supported firms have 7-8% higher within-firm productivity growth rates, compared to similar firms that applied for, but did not obtain these subsidies. These results are persistent in the quarters after treatment. 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 has contributed the most to the aggregate effect of the support policies on firm productivity. We also find that supported firms have a much lower propensity to exit the market relative to similar other firms.

In the aggregate, we find that productivity grew with 6% in 2020. The largest contribution comes from the within-firm productivity growth of survivors. Both subsidized and non-subsidized firms contributed positively to aggregate productivity growth. These results also suggest that the productivity growth of treated firms is not merely a catch-up effect in declining productivity, but rather a boost to aggregate productivity growth in 2020. Within the treated group, we find a deterioration of allocative efficiency in favor of less productive firms gaining market shares, or of smaller firms becoming relatively more productive. However, across groups, we observe a reallocation of market shares from treated to the untreated firms, suggesting a positive effect of creative destruction towards more productive, untreated firms at the level of the economy.

Taken together, these results suggest that the Covid rescue policies have been successful as a rescue operation, both at the firm and at the aggregate level. While there might have been unintended consequences of these policies in terms of supporting infra-marginally productive firms, hampering creative destruction, we do not find much evidence of that in the aggregate. At this stage however, little is known about the long-term impact of these policies.

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Appendix

A. NACE sectors

Table 13 shows a description of the 2-digit NACE codes (Rev 2, 2008) and their aggregations for sparse sectors, and a verbal description of these sector activities.

B. Government Support Measures

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 has responded with an extensive support scheme. A timeline of the measures taken in 2020 is given in Figure 11. 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 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, which are described in detail in Section 2.

C. Additional results

C.1 Summary statistics treated/untreated

Table 14 shows the summary statistics of treated and untreated firms for the year 2019, in natural logs, and demeaned at the industry level. The table shows that treated firms are on average slightly smaller than untreated firms within the same industry, but there is a common support across the whole distribution for each variable.

Table 13: Industry Descriptions

Industry Code NACE Rev. 2	Description	Industry Code NACE Rev. 2	Description
1	Crop and animal production, hunting and related service activities	46	Wholesale trade, except of motor vehicles and motorcycles
2	Forestry and logging	47	Retail trade, except of motor vehicles and motorcycles
3	Fishing and aquaculture	49	Land transport and transport via pipelines
5-9	Mining and quarrying	50	Water transport
10	Manufacture of food products	51	Air transport
11-12	Manufacture of beverages and tobacco products	52	Warehousing and support activities for transportation
13	Manufacture of textiles	53	Postal and courier activities
14	Manufacture of wearing apparel	55	Accomodation
15	Manufacture of leather and related products	56	Food and beverage service activities
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	58	Publishing activities
17	Manufacture of paper and paper products	59	Motion picture, video and television programme production, sound recording and music publishing activities
18	Printing and reproduction of recorded media	60	Programming and broadcasting activities
19-21	Manufacture of coke, refined petroleum products, chemicals and chemical products, basic pharmaceutical products and pharmaceutical preparations	61	Telecommunications
22	Manufacture of rubber and plastic products	62	Computer programming, consultancy and related activities
23	Manufacture of other non-mettalic mineral products	63	Information service activities
24	Manufacture of basic metals	64-66	Financial and insurance activities
25	Manufacture of fabricated metal products, except machinery and equipment	68	Real estate activities
26	Manufacture of computer, electronic and optical products	69	Legal and accounting activities
27	Manufacture of electrical equipment	70	Activities of head offices; management consultancy activities
28	Manufacture of machinery and equipment n.e.c.	71	Architectural and engineering activities; technical testing and analysis
29	Manufacture of motor and vehicles, trailers and semi-trailers	72	Scientific research and development
30	Manufacture of other transport equipment	73	Advertising and market research
31	Manufacture of furniture	74	Other professional, scientific and technical activities
32	Other manufacturing	75	Veterinary activities
33	Repair and installation of machinery and equipment	77	Rental and leasing activities
35	Electricity, gas, steam and air conditioning supply	78	Employment 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	Specialised construction activities	82	Office administrative, office support and other business support activities
45	Wholesale and retail trade and repair of motor vehicles and motorcycles		

Figure 11: Timeline of Covid-19 safety and support measures.

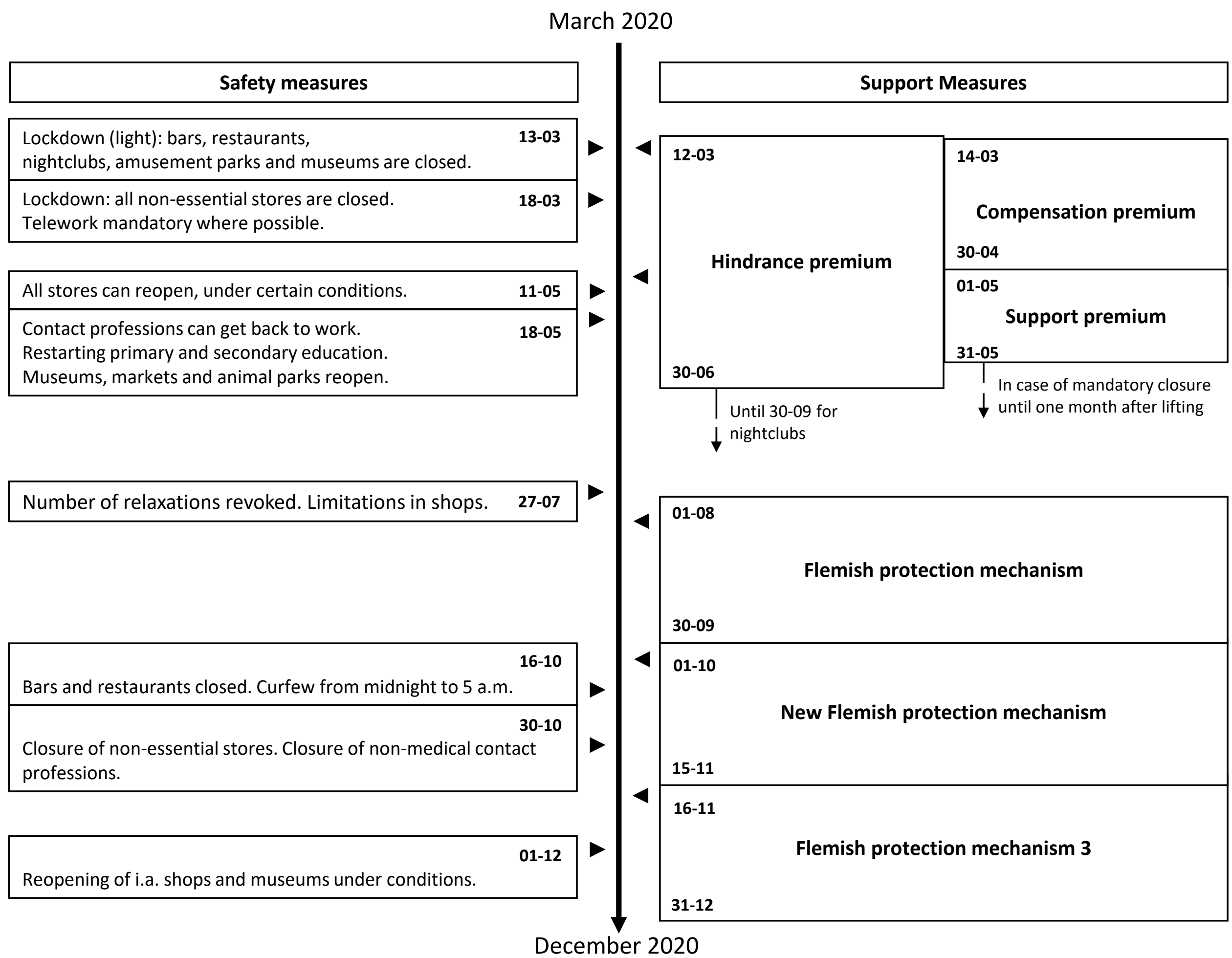
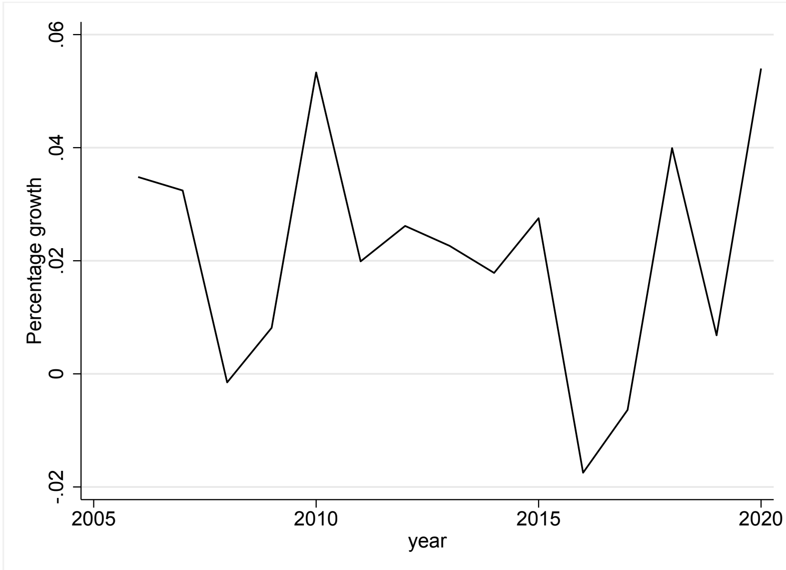


Table 14: Summary statistics treated/untreated, sector demeaned (2019).

	Variable	Mean	Std. Dev.	*percentiles* p10	p50	p90
Treated	Ln Employees (FTE)	0.0	1.3	-1.5	-0.1	1.6
(N = 25,682)	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	Ln Employees (FTE)	0.1	1.2	-1.3	0.0	1.7
(N = 3,681)	Ln Value added	0.2	1.3	-1.3	0.1	1.8
	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 industry averages.

Figure 12: Aggregate growth of productivity, unweighted.



Notes: Yearly growth rates are expressed in percentages. Labour productivity in a given year is calculated as the sum of value added (including negative value added) over the sum of full-time equivalents.

C.2 Aggregate productivity growth

Figure 12 shows the evolution of aggregate labour productivity, measured as the total sum of value added over the total sum of FTE employment when negative value added observations are taken into account. Figure 13 shows the evolution of aggregate labour productivity, measured as a weighted average of firm-level log productivity (Value added/FTE) using value added weights.

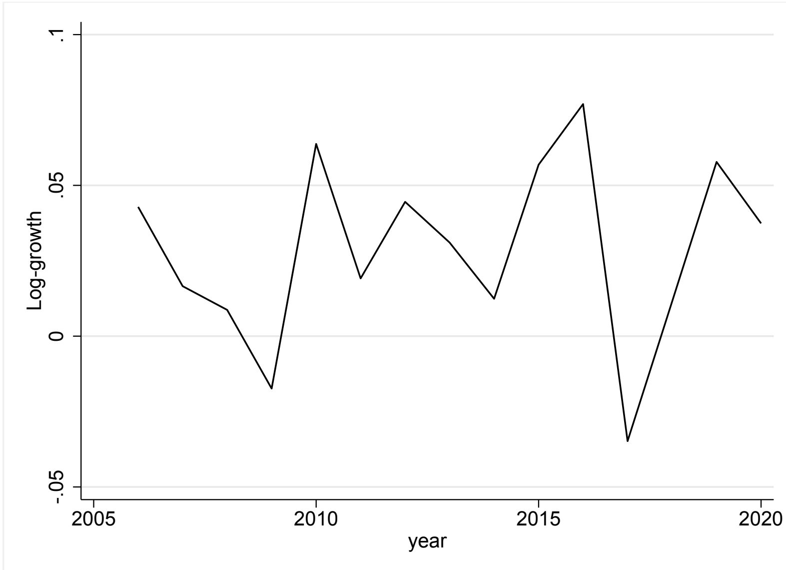
D. TFP

Where labor productivity only counts labor as an input, total factor productivity (TFP) also takes capital into account. TFP for every firm in every year 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, depicted in logarithms:

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

Y stands for the output variable, in this case value added for its broad availability and the direct link to general welfare. The value added production function can be seen as a gross out-

Figure 13: Aggregate growth of productivity, value added weights.



Notes: Yearly growth rates are expressed in percentages. Labour productivity in a given year is calculated as a weighted average of firm-level log productivity (value added/FTE) using value added weights.

put production function that is Leontief in intermediate inputs (Gandhi et al., 2020). Capital is denoted with k and labor with l. The residual is broken down into two terms, ω en ε. 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, but the distinction lies with the firm. Where ω is observed by the firm, ε is unobserved to the firm as well before making its input decisions. That the firm observes the realization of the shock ω 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 & Andrews, 1944). Indeed, labor and capital will be correlated with the ω 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 behaviour 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 & 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 labor and that the function must be strict 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 $E(\omega_{it}|\,\omega_{it-1},...,\omega_{i1}) = E(\omega_{it}|\,\omega_{it-1})$, or $\omega_{it} = g(\omega_{it-1}) + \xi_{it}$. ξ_{it} is thereby called 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:

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

As said before, 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 $\theta_t(m_{it}, k_{it}, l_{it}) = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + f^{-1}(m_{it}, k_{it}, l_{it})$ 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:

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

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's 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:

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

The labor and capital coefficient 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).

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	9.72	11.28	46	0.90	0.05	11.07	11.50
2	0.56	0.22	9.09	11.59	47	0.74	0.12	10.04	11.20
3	1.05	0.03	11.36	11.79	49	0.80	0.11	10.30	11.30
5-9	0.14	0.21	10.39	12.00	50	0.76	0.18	9.88	11.97
10	0.82	0.11	10.16	11.24	51	0.78	0.09	10.89	11.59
11-12	0.50	0.17	10.46	11.70	52	0.83	0.09	10.83	11.57
13	0.73	0.09	10.51	11.16	53	0.83	0.09	10.39	11.16
14	0.59	0.08	10.59	10.95	55	0.62	0.16	9.74	11.39
15	0.90	0.09	10.12	11.07	56	0.66	0.11	10.05	11.13
16	0.78	0.09	10.41	11.22	58	0.76	0.03	11.26	11.31
17	0.87	0.06	10.87	11.34	59	0.79	0.06	11.02	11.49
18	0.74	0.09	10.51	11.29	60	0.56	0.04	11.95	11.56
19-21	0.99	0.07	10.73	11.68	61	1.29	0.06	10.37	11.38
22	0.83	0.11	10.37	11.34	62	0.88	0.04	11.07	11.37
23	1.15	0.07	10.19	11.39	63	1.18	0.02	10.92	11.33
24	0.68	0.13	10.56	11.45	64-66	1.17	0.04	11.11	11.63
25	0.80	0.09	10.54	11.32	68	0.21	0.14	10.30	11.87
26	1.01	0.06	10.65	11.47	69	0.80	0.07	10.91	11.60
27	0.67	0.08	11.02	11.30	70	0.47	0.09	10.94	11.70
28	0.93	0.07	10.65	11.38	71	0.81	0.08	10.75	11.47
29	0.95	0.06	10.71	11.32	72	0.97	0.08	10.68	11.60
30	1.01	0.07	10.59	11.45	73	0.85	0.06	10.77	11.35
31	0.74	0.11	10.14	11.11	74	0.78	0.09	10.44	11.31
32	0.79	0.10	10.37	11.24	75	0.66	0.12	10.41	11.76
33	0.79	0.07	10.82	11.37	77	0.42	0.22	9.55	11.77
35	0.22	0.19	11.19	12.62	78	0.81	0.05	10.91	10.91
36-39	0.18	0.16	11.02	11.62	79	0.86	0.07	10.51	11.14
41	1.46	0.02	10.68	11.37	80	0.77	0.07	10.72	11.23
42	0.79	0.10	10.53	11.39	81	0.76	0.10	10.43	11.41
43	0.78	0.09	10.43	11.30	82	0.73	0.07	10.83	11.47
45	0.83	0.11	10.24	11.33					