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The Impact of Financial Support to Firms During Crises: The Case of Covid Aid in the EU*

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Abstract

The Covid-19 pandemic caused a global economic crisis, leading governments to provide substantial State Aid to support firms. This paper examines the effectiveness of Covid-related financial support in Spain and Italy, focusing on its impact on firm recovery. Using a difference-in-differences (DiD) approach combined with propensity score weighting, it compares outcomes of similar firms receiving aid to those without. The results show significant benefits for micro-firms, including mitigated turnover declines and increased investments in both tangible and intangible assets. The findings highlight the critical role of government support in business survival and recovery, especially for SMEs, during the pandemic.

Keywords: State Aid; Aid effectiveness; Temporary Framework; Covid; Firm growth; Investment; Difference-in-differences

JEL Classification: D04, D22, L25, L52, P43

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1 Introduction

The Covid-19 pandemic triggered a severe global economic crisis, disrupting entire value chains, industries, and markets, particularly in sectors reliant on face-to-face activities, which experienced unprecedented revenue declines and faced the risk of mass bankruptcies. In response, governments worldwide introduced significant financial support measures to provide immediate liquidity, stabilise at-risk companies, and safeguard jobs, with the goal of preserving economic structures and laying the foundations for recovery once activity resumed.

The European Commission swiftly established a Temporary Framework (TF) for State Aid that enabled support for viable firms facing temporary pandemic-related challenges while excluding firms already in financial distress before the crisis, thereby avoiding distortions of competition in the Single Market.¹ The TF was particularly focused on supporting small and medium-sized enterprises (SMEs), which were considered more vulnerable to the economic impact of the pandemic.² To ensure that support was tailored to the needs of each firm and was proportional to the minimum amount needed to survive the pandemic, the TF set limits on the amount of aid that could be received, thereby preventing excessive support. As the pandemic evolved, the TF was revised multiple times to adapt to the changing economic context, with amendments such as raising aid caps, introducing new financial instruments, and adjusting eligibility criteria to better target firms in need.³

This study assesses the impact of Covid State Aid on firm performance in Spain and Italy, two EU Member States which received substantial support under the TF. Using a difference-in-differences (DiD) model combined with propensity score weighting (PSM), we estimate the effects of receiving financial assistance by comparing aid recipients with a matched group of non-recipient firms with similar pre-crisis characteristics. This mitigates the potential endogeneity due to the selection of firms into treatment.⁴ The analysis focuses on firm outcomes one to two years after receiving the aid. A two-way

¹While State Aid is generally prohibited under Article 107(1) of the Treaty on the Functioning of the European Union (TFEU), exceptions are allowed during severe economic disturbances, as outlined in Article 107(3)b.

²The definition of a ‘firm in difficulty’ provided by the European Commission is multifaceted (see Section A.1 in Appendix), and it is challenging to identify such firms using existing datasets. The data would need to encompass both balance sheet data and firm-specific information on the legal company type, as well as potential insolvency proceedings. For a general overview of the State Aid Temporary Framework, see https://competition-policy.ec.europa.eu/state-aid/coronavirus/temporary-framework_en

³For details on the TF amendments, see Section A.1 in Appendix.

⁴Harasztosi et al. (2022) show that Covid aid beneficiaries tend to be led by executives who are more optimistic about their future investment plans, suggesting a self-selection of more resilient and forward-looking firms into the treatment. In fact, the non-take-up of government aid by some firms was largely voluntary, indicating that many either did not need the aid or chose alternative coping strategies.

fixed effects (TWFE) model is employed to control for both firm-specific and time-specific heterogeneity, while an event study approach is used to identify the dynamic effects of aid over time. Additionally, we assess the robustness of our results to alternative estimators.

We use a comprehensive dataset that combines firm-level balance sheet information from Moody's/Bureau van Dijk's Orbis database with administrative records of aid recipients from the National Registries (NRs) in Italy and Spain. These two countries were particularly hard hit by the Covid-19 pandemic, facing severe health crises and economic challenges more pronounced than in many other European countries. Both experienced early and aggressive outbreaks that overwhelmed healthcare systems and required strict and prolonged lockdowns. Spain's GDP contracted by 10.8% in 2020, while Italy's one shrank by 8.9%, both exceeding the downturns in larger EU economies such as Germany and France. In response to the crisis, Italy and Spain rolled out significant aid packages. Spain's Covid aid to businesses was 7.3% of its GDP in 2020, higher than the EU average of 3.3%. Italy's aid was around 6% of its GDP.

These policy responses placed both countries among the highest proportionate spenders in Europe, reflecting the severe challenges they faced and the scale of government intervention required to mitigate economic collapse. Moreover, the high levels of public debt in both countries compounded the difficulty of their fiscal responses, making it harder for them to sustain support for firms and workers compared to wealthier or more financially resilient nations. While their stimulus packages included direct support, both countries made extensive use of loan guarantees. Despite these commonalities, Italy and Spain experienced the Covid-19 crisis in different economic and policy contexts, making their comparison particularly insightful. Italy, with its larger manufacturing sector and higher public debt, faced more acute liquidity constraints, which delayed its policy response. While slower to respond initially, Italy later made extensive use of State Aid, reaching a larger proportion of beneficiaries. In contrast, Spain's response was swifter, making use of *de minimis* aid to provide rapid relief to firms (Canzian et al., 2024).

The results of the analysis suggest that Covid aid effectively helped firms recover in both Italy and Spain. Recipients' firms were those hit more by the crisis as the decrease in turnover was larger than non-recipients. However, this gap disappeared by 2021 and turned positive (2.7%) by 2022. The impact of Covid aid varied significantly by firm size, with micro-firms being the primary drivers of the overall positive effects observed in both countries. In Italy, micro-firms experienced stronger and more immediate benefits, with a measurable increase in turnover already in 2021. In contrast, in Spain, the positive impact on turnover did not become statistically significant until 2022. By that year, the effect of aid in Italy was five times greater than in Spain, corresponding to a 5% increase in turnover compared to just 1% in Spain.

Importantly, and perhaps unexpectedly, Covid aid led to significant investment, increasing firms' total assets with annual growth rates ranging from 5% to 7% between 2020 and 2022. This growth reflects more than just cash inflows, as both tangible and intangible fixed assets grew significantly, indicating strong investment activity. Intangible assets grew faster than tangible ones, suggesting that firms focused more on innovation and digitalization in response to the pandemic.⁵

Finally, sectoral analyses shows that construction firms benefitted more from Covid aid, with significant improvements in turnover, gross fixed capital formation, and employment in both countries. In Spain, construction firms showed a balanced investment in both tangible and intangible assets, indicating a potential focus on digitalization and technology integration. In contrast, Italian firms concentrated more on tangible investments, particularly in construction and wholesale trade. These patterns suggest different strategic responses to the crisis, with Italian firms prioritizing physical infrastructure, while Spanish firms focused on technological upgrades. Furthermore, multiple rounds of aid did not have a multiplicative effect on outcomes, indicating that the timing and distribution of aid were more critical than its frequency.

Our study contributes to the limited but growing empirical literature assessing the effectiveness of government support to firms during the Covid-19 pandemic, focusing on short-term outcomes such as turnover and labour productivity. While the broader literature on State aid is extensive and heterogeneous in terms of methods, outcomes, and contexts, systematic evidence on Covid aid remains relatively scarce and fragmented. Recent research has provided mixed but generally positive results on the short-term impact of pandemic support. For instance, Harasztosi et al. (2022) show that Covid aid in the EU was effective in supporting investment, maintaining financial stability through recapitalisation, and fostering digital transformation. Similarly, Konings et al. (2023), examining a Belgian region, found positive but transitory effects on productivity and firm survival. Studies such as Bighelli et al. (2023) and Harasztosi et al. (2022) suggest that aid was predominantly allocated to firms severely affected by the crisis, rather than those with pre-existing weaknesses. Moreover, Audretsch et al. (2025), Bertsek et al. (2024) and Block et al. (2022) provide evidence of increased survival probability among SMEs and the self-employed across a range of European countries, although with considerable heterogeneity depending on sector, education, and risk tolerance.

These findings resonate with earlier evidence on the effects of public grants to SMEs, as documented in the systematic review by Dvouletý et al. (2021), which highlights a generally positive impact on survival, employment, tangible assets and sales, but more mixed

⁵This is consistent with studies showing how the adoption of digital tools determined firms' survival during and after the crisis (e.g. Audretsch et al., 2025).

outcomes on productivity. Crucially, they also underscore the importance of firm characteristics and time horizon in mediating these effects. Methodologically, many studies rely on matching techniques combined with DiD, with fewer applying alternative causal inference strategies such as Regression Discontinuity Designs or Heckman selection models. In this context, our analysis offers a valuable contribution since we rely on detailed administrative data covering the universe of State aid beneficiaries in two EU Member States –Italy and Spain– which allows us to define treated and control groups with a high degree of precision over a five-year period (2017-2021). This level of granularity is uncommon in cross-country studies of Covid aid. Our findings are broadly in line with those of Konings et al. (2023), in that we observe positive short-term effects on firm outcomes without direct evidence of creative destruction or growth. However, our broader cross-country scope and richer outcome variables allow for more generalizable insights. In sum, we contribute new empirical evidence on the targeting and short-term effectiveness of Covid aid, while offering a framework that can be extended to retrospective evaluations of other emergency support programmes in the EU.

2 Data

This study combines firm-level data from two sources: Orbis, provided by Moody’s Analytics – Bureau Van Dijk (BvD), and the National Registers (NRs) of State Aid for Spain and Italy. Orbis compiles financial and operational information from corporate accounts across multiple countries and sectors (excluding agriculture and public services). It includes key variables relevant to this study, such as firms’ turnover, number of employees, and asset composition, e.g. tangible, intangible, and current assets. Orbis is widely used in empirical research for its detailed firm-level coverage, although it has known limitations in cross-country representativeness and data completeness. These issues are less pronounced for Italy and Spain, where coverage is comparatively more comprehensive (Bajgar et al., 2020). To enhance representativeness and minimise data quality issues, we follow the cleaning procedures recommended by Kalemli-Özcan et al. (2022) as detailed in Section 2.1.

The National Registers of State Aid are official administrative sources provided by the Italian and Spanish Ministries of Economy and Finance.⁶ They record all firm-

⁶Canzian et al. (2024) also examined the potential of utilizing an alternative data source made available by the European Commission—the Transparency Award Module (TAM) dataset—which covers all EU member states. However, the authors find that this alternative source lacks the precision and granularity required to accurately identify aid beneficiaries due to non-mandatory reporting thresholds. This limitation is evident even in the case of Italy, a country with relatively high compliance in reporting to the TAM database.

level State Aid awards granted from 2017 onward, including recipient name, location, identifier, sector, type of aid (e.g. grant, loan, guarantee), legal reference, and date of award. Importantly, the award date allows for precise identification of treatment timing. However, while the NRs provide the award date for each aid –the date when a firm becomes legally entitled to receive a financial transfer–, they do not track the actual transaction date.⁷ Covid-related aid is identified in this dataset through State Aid reference numbers and, where necessary, through the stated objective of the aid. Between 2017 and 2022, the NRs report 11.3 million aid awards to over 819,000 firms in Spain, and 10.2 million awards to 3.1 million firms in Italy.

The data allow us to clearly identify each firm’s treatment status over the 2017-2022 period. For this study, we focus on comparing firms that received only Covid aid granted after 2019 with those that received no State Aid during the entire period. Thus, while the National Registers include firms that received non-Covid aid at some point, these firms are excluded from the main analysis to ensure a more focused and consistent comparison between treated and untreated firms. Although State Aid data are available for the 2017-2022 period, we rely on Orbis data covering 2015-2022 to capture pre-Covid trends, align with the timing of treatment information, and include two additional years to ensure sufficient coverage for post-treatment evaluation.

2.1 Sample

We link the National Registers of State Aid to Orbis using firms’ national identifiers. Following Kalemli-Özcan et al. (2022), we perform cleaning procedures for reporting dates, removal of duplicates, exclusion of consolidated accounts, and removal of outliers (e.g. firms with negative turnover or implausibly high values). Additionally, we exclude observations from sectors with poor data coverage, such as agriculture, public administration, finance, and insurance. As mentioned earlier, firms that received non-Covid-related State Aid are also excluded to ensure a focused analysis, as these firms were subject to different policy treatments. Finally, firms with missing size classifications or key financial variables are removed from the sample.

For the main analysis, we focus on a balanced panel, retaining only firms for which data is available across all years from 2015 to 2022. This approach enables us to track within-firm performance over time, consistent with other studies in the field (e.g. Konings et al. 2023). The use of a balanced panel is particularly important for capturing financial information during the entire pre-treatment period (2015-2019), which helps control for factors influencing selection into treatment. This is crucial, as the Temporary Framework

⁷There may be a time lag between the legal entitlement and the actual payment of the aid, and the extent of this lag is unknown. This has implications for the analysis as discussed in Section 4.

(TF) stipulates that firms receiving aid must not have been in financial difficulty for several years before 2020. Finally, the balanced panel may enhance better comparability between treated and control firms and reduce selection bias into treatment, as discussed in Section 5.3.

However, using a balanced panel may raise concerns about omitting the potential role of the aid on post-treatment survival.⁸ To address this, we first analyse differences in characteristics between firms that drop out of the sample between 2020 and 2022 and those that remain in the balanced sample. As the former group exhibits differences in terms of size, capital levels, EBIT, and sectoral distribution (see Table A3 in Annex A.2), we conduct a separate analysis of post-treatment firm exit in Section 5.3.⁹

2.2 Firms' characteristics and treatment status

Table 1 reports the descriptive statistics on firms' characteristics by treatment status (Covid aid beneficiaries and non-beneficiaries) and year of treatment. In Spain, the vast majority of aid recipients received support in 2020, accounting for 86% of the treated firms in the sample. In contrast, the distribution of aid in Italy was more spread over time, with 51.3%, 39.1%, and 9.6% of firms receiving aid in 2020, 2021, and 2022, respectively (see Table A4 in the Appendix).

In both countries, firms that received aid in 2020 tended to be smaller across almost all observed dimensions compared to those that received aid at later stages. This pattern was particularly pronounced in Italy, where the average turnover of firms receiving Covid aid in 2022 was €20.3 million, compared to €1.9 million for those supported in 2020. This difference reflects the evolution of the Temporary Framework, which underwent several revisions during the pandemic. Notably, in 2022, its scope was expanded to include support for firms pursuing digital and green transitions.¹⁰ Focusing on the sectoral distribution of beneficiaries in 2020, Italy had a larger proportion in manufacturing (29.3%) than Spain (24.7%). In contrast, 33.6% of treated firms in Spain operated in the wholesale sector compared to 27.8% in Italy. This distribution remained stable over time. Remarkably, a lower proportion of Italian firms received support in retail in 2021 (14.4% of beneficiaries) compared to 2020 (19.3%). Finally, the 2020 beneficiaries appeared to be larger than non-beneficiaries in terms of turnover, total assets, and capital.

⁸Notice that, owing to reporting lags of up to five years in Orbis, a firm's disappearance from the dataset does not necessarily indicate market exit.

⁹Additionally, we conduct sensitivity analyses on a subsample of firms that is balanced in the pre-treatment period (i.e., firms that are always observed between 2015 and 2019) but unbalanced in the post-treatment period (i.e., firms that may or may not drop out of the sample during 2020–2022). The results from these analyses remain largely consistent with the main findings of our preferred specification.

¹⁰See Appendix A.1 for a detailed discussion of the Temporary Framework and its amendments.

Table 1: Firm's characteristics by year of treatment

Country		Spain				Italy							
When first treated?	Never	2020	2021	2022	Never	2020	2021	2022	Never	2020	2021	2022	Never
	%	%	%	%	%	%	%	%	%	%	%	%	%
<i>Size</i>													
Micro	82.5%	79.8%	85.1%	83.9%	72.8%	85.8%	71.9%	65.4%					
Small	12.7%	16.0%	13.1%	13.1%	20.5%	11.6%	22.8%	23.4%					
Medium	3.7%	3.7%	1.6%	2.2%	5.1%	2.2%	4.4%	7.9%					
Large	1.1%	0.5%	0.2%	0.7%	1.7%	0.4%	0.9%	3.3%					
<i>Sector</i>													
Manufacturing	24.8%	24.7%	25.3%	29.0%	32.7%	29.3%	32.2%	30.9%					
Construction	25.7%	22.3%	21.6%	24.3%	19.4%	23.7%	21.4%	18.2%					
Wholesale	30.6%	33.6%	32.1%	30.2%	34.1%	27.8%	32.1%	33.3%					
Retail	18.9%	19.4%	21.1%	16.6%	13.9%	19.3%	14.4%	17.7%					
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean
No. employees	13.848	4.000	11.484	5.000	7.917	5.000	25.433	5.000	13.428	4.000	6.671	4.000	10.404
Turnover (€million)	4.791	0.492	2.618	0.679	1.822	0.557	4.020	0.663	7.850	0.839	1.963	0.607	3.941
Total assets (€million)	3.243	0.415	1.830	0.504	1.212	0.419	3.384	0.486	6.262	0.758	1.557	0.500	3.223
Current assets (€million)	2.123	0.283	1.260	0.332	0.838	0.282	2.148	0.333	4.530	0.592	1.198	0.389	2.413
Fixed assets (€million)	1.120	0.078	0.569	0.114	0.374	0.086	1.236	0.100	1.732	0.062	0.359	0.051	0.809
Capital (€million)	0.293	0.012	0.129	0.015	0.112	0.012	0.355	0.012	0.428	0.020	0.075	0.011	0.208
Loans (€million)	0.084	0.000	0.250	0.013	0.043	0.000	0.370	0.000	0.181	0.000	0.172	0.000	0.139
Material costs (€million)	3.535	0.238	1.850	0.352	1.283	0.275	2.116	0.292	4.879	0.323	1.217	0.246	2.378
Observations	32,206		24,342		3,484		404		8,992		17,734		13,539

Notes: The table reports summary statistics for firms receiving Covid Aid (treated), by year of treatment, and firms not receiving any aid (untreated) in the final sample, for both Italy and Spain.

Given the above, firms that first received Covid aid in 2020 are likely to differ from those that benefited in subsequent years. Moreover, as the TF was extended and revised multiple times, the analysis of aid allocated in 2021 may be subject to endogeneity concerns. To mitigate this risk –particularly the potential for anticipatory effects among firms treated later in the pandemic (i.e. in 2021 or beyond)– the main analysis focuses on firms that first received aid in 2020. This also implies that the study design is non-staggered, as the treatment period is the same for all beneficiaries. While the focus remains on 2020 recipients, we also present results for firms receiving aid in 2021 or later in Section 5.2.

3 Identification Strategy

In this section, we present our identification strategy to measure the causal impact of the aid on various measures of firm performance. Despite the pandemic hitting firms exogenously and unpredictably, participation in the financial support programme was voluntary, implying that recipient firms may differ from non-applicants in both observable and unobservable characteristics. To address potential endogeneity arising from selection into treatment, we adopt a difference-in-differences (DiD) approach combined with propensity score matching (PSM), thereby exploiting the advantages of both methods. On the one hand, controlling for observable pre-treatment characteristics increases comparability between the treated and control firms while helping to satisfy the parallel trends assumption. On the other hand, leveraging the longitudinal nature of the data allows us to account for time-invariant unobserved heterogeneity.

3.1 Propensity Score Matching

To address potential selection bias arising from differences in observable characteristics as shown in Table 1, we implement propensity score matching (PSM). This method, which is described in Appendix A.3.1, mimics random treatment assignment by conditioning on a comprehensive set of pre-treatment observable characteristics, under the assumption of selection on observables.

We estimate the likelihood of receiving aid –the propensity score– by specifying a probit model that includes pre-pandemic firm characteristics such as size, sector, geographical location, and financial indicators.¹¹ Given the substantial heterogeneity in the data, only a small number of firms fall outside the common support region, which are

¹¹After evaluating the balancing properties of the control variables across several matching algorithms, we chose a four-nearest neighbour (NN) matching method with replacement, coupled with a tight caliper setting of 0.001. The results of the matching procedure and diagnostic tests are presented in section A.3.1 in the Appendix.

then excluded from the sample. Post-matching diagnostics indicate good balancing, with mean differences between treated and untreated firms below 2% and variance ratios close to one. Moreover, by using the propensity scores to re-weight non-treated firms in the DiD regression, we better approximate a counterfactual scenario where treated and untreated firms are comparable thus ensuring a more credible estimation of the treatment effect.

3.2 Difference-in-differences

While we compare firms with similar observable characteristics, selection on unobservables remains a potential concern. Unobservable factors –such as managerial skills, risk preferences or internal investment strategies– may also play a role in the decision to apply for aid. To address this concern, we use a DiD approach and estimate a two-way fixed effects (TWFE) model that allows to account for time-invariant unobserved heterogeneity. Specifically, we use the following event study specification:

$$Y_{ist} = \sum_{r=-5, r \neq -1}^2 \delta_r \times 1[R_{i,t} = r] + \alpha_i + \mu_t + \lambda_{st} + \varepsilon_{ist}, \quad (1)$$

where Y_{ist} is the outcome of firm i in sector s at time t ; the term $R_{i,t}$ indicates the time relative to the treatment for firm i , where: $R_{i,t} = 0$ is the year of implementation; negative values $R_{i,t}$ (e.g., -1 to -5) represent pre-treatment periods and positive values (e.g., 1 to 2) represent the post-treatment periods. $R_{i,t} = -1$ (2019) is taken as the reference year. The coefficient δ_r captures the effect for each period relative to treatment across firms, in an event study setting. The error term ε_{it} is assumed to be arbitrarily correlated at the firm level to capture potential serial correlation or heteroscedasticity. The terms α_i and μ_t represent firm and year fixed effects that control for time-invariant unobserved firms characteristics and time-specific common factors, respectively. Moreover, considering sector-within-year fixed effects, captured by λ_{st} , allows accounting for unobserved heterogeneity unique to each sector in a given year.¹² To ensure comparability, observations are weighted by the inverse of their propensity scores, assigning greater weight to firms with lower likelihood to receive treatment based on observables.

In our event study setting, the coefficients on the negative $R_{i,t}$ terms test the validity of the parallel trends assumption by indicating the absence of any anticipation effects.

¹²The results are also tested against the inclusion of region-within-year fixed effects instead of sector-year fixed effects and are not affected by this change. The two sets of fixed effects cannot be included simultaneously due to collinearity.

While we account for substantial heterogeneity between treated and control firms, pre-treatment differences may still arise due to unobserved time-varying confounders, potentially violating this assumption. This concern has been widely discussed in the recent DiD literature, which has proposed alternative estimation strategies to address such issues.¹³ Among these, the Callaway and Sant’Anna (CS) estimator (Callaway and Sant’Anna, 2021) –though primarily designed for staggered adoption settings– may offer valuable insights in our context. Unlike standard DiD approaches, the CS estimator relies on a conditional parallel trends assumption, allowing for unconditional pre-treatment trend differences across groups. Specifically, it assumes that, conditional on covariates, the average outcomes of treated and control units would have followed similar trajectories in the absence of treatment. This makes it more flexible in scenarios where pre-treatment trends differ across groups.

Given our non-staggered setting and the need to control for pre-treatment characteristics over the entire pre-treatment period, we prefer the two-way fixed effects (TWFE) model as it offers a more efficient approach. Nonetheless, we also contrast it with the CS approach to assess the robustness of the results. For the CS estimator, we adopt the matching method based on the inverse probability weighting proposed by Abadie (2005). However, our results are robust to the use of the doubly robust DiD estimator based on stabilised inverse probability weighting and ordinary least squares of Sant’Anna and Zhao (2020).

4 Main results

This section presents the results on the impact of Covid Aid on various measures of firm performance, including operating turnover, employment, investment, and financial indicators such as profitability and labour productivity. To deepen our understanding of the underlying mechanisms, we also explore a set of extensions and heterogeneity analyses. The main results are based on the matching with Difference-in-Differences (DiD) method described above, accounting for pre-treatment outcomes. Section 4.1.2 compares different models with and without these corrections to assess the influence of pre-treatment differences on the results.

The models are set within an event study framework, where the impact of the aid is reported for the years 2020 (the year of policy implementation), 2021, and 2022 (the two post-treatment years). This approach allows for the examination of short-term dynamics and the evolution of the aid’s impact over time, with 2019 serving as the baseline year.

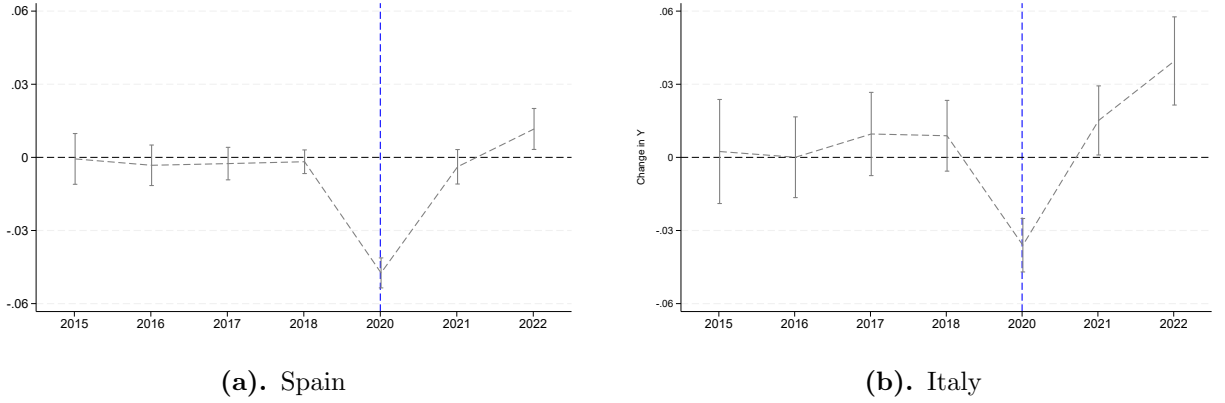
¹³A detailed discussion of the strengths and weaknesses of these estimators can be found in Roth et al. (2023).

Moreover, it allows examining pre-treatment differences to assess potential anticipatory effects and parallel trends violations.

4.1 The Impact of Covid Aid on Turnover

Figure 1 shows the impact of Covid Aid on turnover, revealing similar patterns for Spain and Italy. In both countries, beneficiary firms experienced lower turnover in 2020 compared to non-beneficiaries-by approximately 4% in Spain and 3% in Italy. This negative gap narrowed over time: the estimated coefficients were no longer statistically different from zero in 2021 and turned positive in 2022, reaching 2.7% in Spain. The recovery in Italy is even more pronounced, with treated firms exhibiting a turnover increase of over 1% in 2021 and more than 4% in 2022. In both countries, none of the lead terms are statistically significant, suggesting no evidence of anticipatory effects and supporting the validity of the parallel trends assumption, conditional on observable characteristics.

Figure 1: The effect of receiving Covid-Aid on firms' turnover



Notes: Each panel displays on the y-axis the coefficient obtained from the estimation of the matching-DiD model for turnover. The vertical bars represent 95% asymptotic confidence intervals. Regressions include fixed effects and controls as from Equation 3.2.

4.1.1 Comparing firms with similar sales shocks in 2020

The results show that aid had a positive impact on beneficiaries' turnover two years after implementation, despite a sharper decline in their turnover in 2020 compared to non-beneficiaries. This likely reflects the delayed impact of support measures on beneficiaries, who were on average more affected by the crisis. While the Covid-19 crisis began early in 2020, the Member States required time to implement the necessary administrative procedures. For example, national reports indicate that much of the aid-especially in Italy-was disbursed in the second half of the year (see Section 2.2). Moreover, the support primarily took the form of guaranteed loans (Canzian et al., 2024), which tend to affect

firms' revenues with a lag, as these instruments improve liquidity and access to credit but do not translate immediately into higher sales. The divergence in turnover in 2020 between beneficiaries and non-beneficiaries may also be partly attributable to the time and resources the former spent on applying for and securing the aid - an administrative burden that likely diverted attention from core business activities. This effect may have been more pronounced for smaller firms with limited managerial capacity, while larger firms were better positioned to absorb the costs of accessing support without significantly disrupting operations - ultimately increasing their likelihood of obtaining the aid (Luma and Ademi, 2023).

To better isolate the effect of aid from the differential impact of the pandemic on beneficiaries, we re-estimate the model within more homogeneous groups of firms, classified by the extent of their sales decline in 2020. The decline in sales is commonly used to capture the strength of the crisis's impact on firms (e.g. Harasztosi et al., 2022). Firms are divided into five categories based on their 2020 sales performance: three groups with declining sales (30-60%, 15-30% and 0-15%) and two groups with increasing sales (0-20% and 20-100%). The distribution of sales variation between treated and control firms is shown in Table A2 in the Appendix.

Table 2: Effect of Covid-Aid on turnover by different categories of 2020 sales' drop

Spain					
Drop in sales category	Decrease 30-60 %	Decrease 15-30 %	Decrease 0-15 %	Increase 0-20 %	Increase 20-100%
Treat x 2020	-0.005 (0.004)	-0.002 (0.001)	-0.002 (0.001)	0.003 (0.001)	0.013*** (0.001)
Treat x 2021	0.048*** (0.012)	0.019*** (0.005)	0.014*** (0.004)	0.020*** (0.005)	0.036*** (0.10)
Treat x 2022	0.062*** (0.015)	0.022** (0.008)	0.029*** (0.006)	0.020** (0.007)	0.063*** (0.015)
N	62,248	100,592	126,392	97,608	46,984
Italy					
Treat x 2020	0.002 (0.008)	0.005 (0.004)	0.001 (0.004)	0.003 (0.004)	0.007 (0.012)
Treat x 2021	0.078*** (0.016)	0.047*** (0.011)	0.026*** (0.008)	0.049*** (0.011)	0.044 (0.024)
Treat x 2022	0.091*** (0.027)	0.034* (0.016)	0.053*** (0.010)	0.050*** (0.015)	0.073* (0.031)
N	35,224	48,384	55,048	36,376	17,272

Notes: The table reports the estimated coefficients of the matching-DID model for turnover, by treatment year across different ranges of sales variation measured in 2020 for Spain and Italy. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

This stratification allows us to examine whether the aid impact varies according to the

intensity of the sales shock experienced in 2020, which serves as a proxy for the severity of the effect of the crisis on the firm. Table 2 shows that, by estimating the effect within sales shock categories, we disentangle the impact of the aid from the crisis effect of 2020. This is reflected in the small and almost all non-significant estimated coefficients in 2020.

Moreover, after accounting for the crisis component in 2020, the impact of Covid Aid on turnover in 2021 and 2022 in Italy remains positive and significant across all sales shock categories, except for firms that experienced a sales increase of more than 20% in 2020. In Spain, the results indicate that the aid effectively increased the turnover of beneficiaries in 2021 and 2022 across all sales categories. In conclusion, these dynamics, with increasing effects in 2021 and 2022, mirror those observed in the main specifications.

4.1.2 Comparison across estimators and specifications

The full set of obtained results is presented in Tables A8 and A9 in Appendix A.3. Our preferred specification is the propensity score-weighted TWFE estimator described in Section 3, which conditions on a rich set of pre-pandemic firm characteristics and uses the full 2015-2019 period to construct the counterfactual trend. This model is chosen as our main identification strategy because it fully exploits the panel structure of the data controlling for time-invariant unobserved heterogeneity through firm fixed effects. We observe a sharper decline in turnover for aid beneficiaries relative to non-beneficiaries in 2020, followed by a gradual recovery over the subsequent two years.

To assess the robustness of these findings and evaluate the potential impact of violations to the parallel trends assumption, we implement a set of alternative specifications. Specifically, we compare the TWFE estimates with those obtained using the Callaway and Sant’Anna (CS) estimator. One key difference is that the CS estimator identifies treatment effects relative to the last pre-treatment year (2019), while the TWFE model averages over the entire pre-treatment period. For both approaches, we also estimate augmented specifications that include firms’ pre-treatment outcomes among the matching covariates. Conditioning on lagged outcomes mitigates dynamic selection concerns and effectively shifts the identifying assumption from conditional parallel trends to conditional mean independence.¹⁴ These robustness checks yield somewhat attenuated treatment effects, especially for the Italian sample, suggesting that pre-existing differences may have played a role and should not be ignored. Nonetheless, the estimated dynamics are consistent across specifications, with a modest strengthening of the effect over time. The close alignment of TWFE and CS estimates reinforces the robustness of our conclusions and highlights the value of accounting for pre-treatment trend divergence in empirical

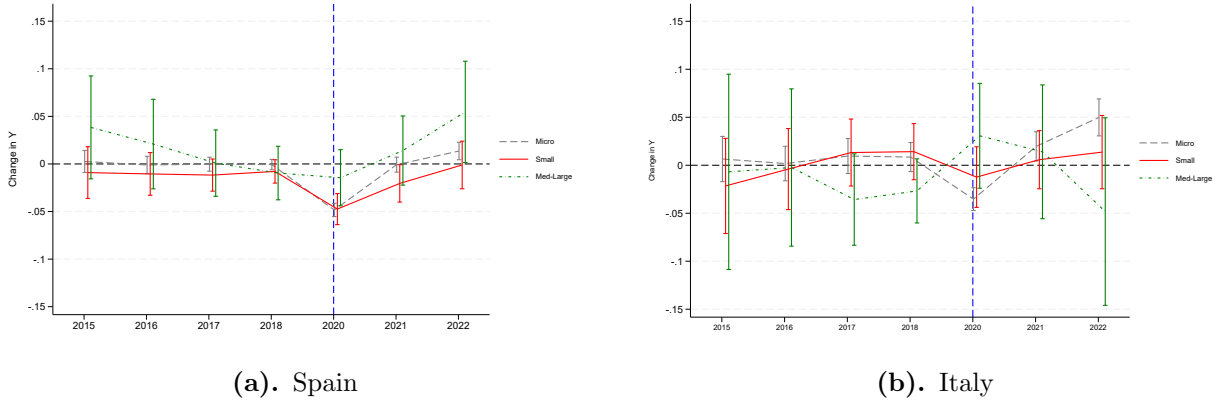
¹⁴When lagged outcomes are included in Z_i , the identifying assumption implies that treatment is effectively random conditional on those outcomes and other characteristics in Z_i .

analyses.

4.1.3 Heterogeneity of results by firm size

Given that Covid Aid placed particular emphasis on supporting small firms, we analyse its impact by stratifying the sample into three firm size categories: micro, small, and medium-large.¹⁵ Figure 2 illustrates the results of this stratification. We estimate a statistically significant positive effect of Covid Aid on turnover in 2022 for micro firms, suggesting that the results from the pooled sample (Figure 1) are primarily driven by this group of firms. Additionally, the timing and intensity of the aid’s impact on micro firms vary between the two countries. In Spain, turnover among beneficiaries recovered as early as 2021, but its impact was smaller in 2022 (1%) compared to Italy (5%).

Figure 2: The effect of receiving Covid-Aid on firm’s turnover, by firm size



Notes: Each panel displays on the y-axis the coefficients obtained from the estimation of the matching-DiD model for turnover on sub-samples constructed according to firms classes measured by the average turnover reported in the three years before the pandemic. The vertical bars represent 95% asymptotic confidence intervals. Regressions include fixed effects and controls as from Equation 3.2.

The results for medium and large firms are particularly noisy and statistically insignificant. This also holds when analysing the impact of Covid Aid on other variables, particularly employment, labour productivity, total assets and profitability, which are discussed in the following sections.¹⁶ Therefore, in the remainder of the paper, we focus solely on the subset of micro-small firms to conduct these additional analyses, aiming to investigate the mechanisms underlying our main results.

¹⁵The definition of firm size is based on the average turnover reported in the three years prior to the pandemic. Medium and large firms were grouped together due to a small sample size (the distribution of sample sizes is reported in Table 1. The results are robust to alternative definitions of firm size.

¹⁶This is in line with previous studies that have analysed the impact of subsidies and found much larger positive effects on investment for small firms (e.g. Criscuolo et al., 2019).

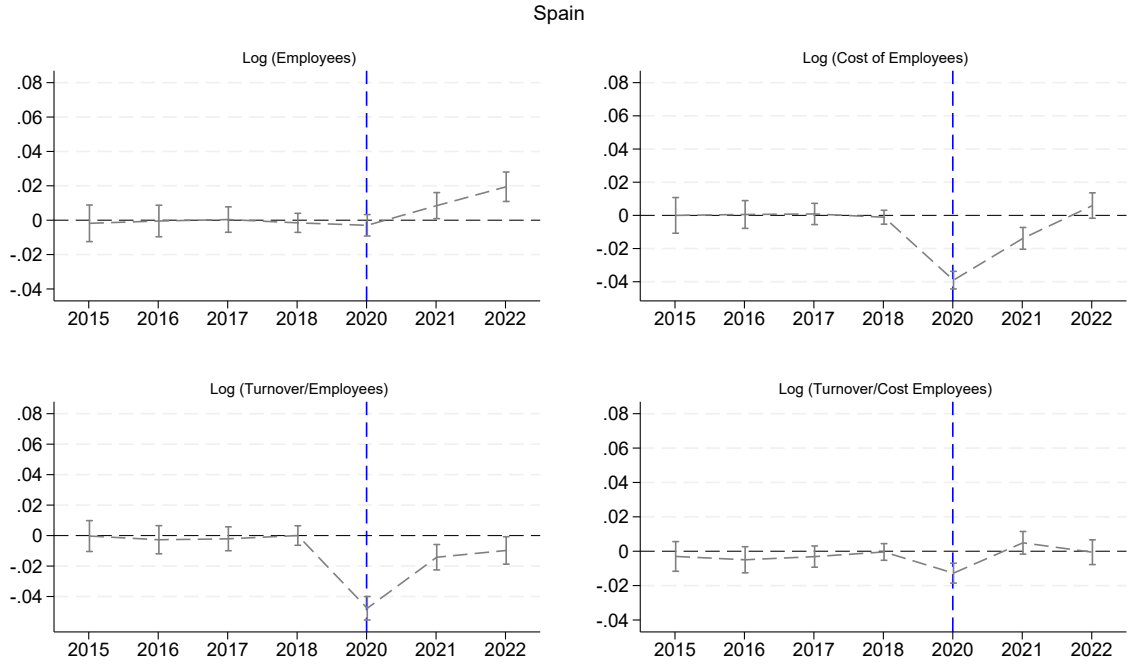
4.2 Other Outcomes

To gain deeper insights into how firms used Covid-Aid and its subsequent effects, the following sections examine the impact of this financial support on key metrics such as employment, labour productivity, investment, and profitability. This analysis aims to uncover the mechanisms through which the aid affected firms' response and outcomes during the pandemic.

4.2.1 Employment and Labour Productivity

Alongside other objectives such as supporting business continuity, ensuring liquidity, and stabilizing the economy, Covid-Aid measures were also designed to protect employment. In this subsection, we analyse the impact of Covid-19 aid on employment and two measures of labor productivity (namely, the ratio of turnover to employees and turnover to cost of employees). Figures 3 and 4 present our results.

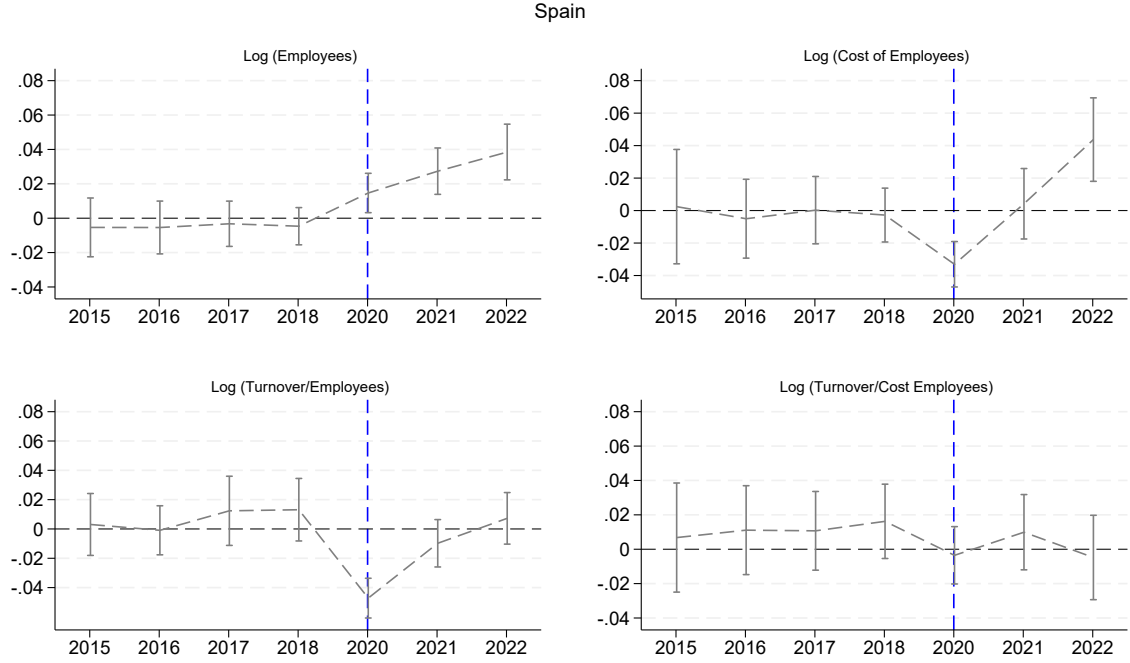
Figure 3: The effect of receiving Covid-Aid on employment and labour productivity - Spain



Notes: Each panel displays on the y-axis the coefficient obtained from the estimation of the the matching-DID model for various employment-related measures, for Spain. We only focus on micro and small firms. The vertical bars represent 95% asymptotic confidence intervals. Regressions include fixed effects and controls as from Equation 3.2.

The top left panel reports the estimated effect of Covid-Aid on the number of employees. Despite a larger decrease in turnover in 2020, Spanish and Italian beneficiaries did not see a reduction in their workforce compared to non-treated firms in that year. In fact, the number of employees even increased in the following two years. This is probably

Figure 4: The effect of receiving Covid-Aid on employment and labour productivity - Italy



Notes: Each panel displays on the y-axis the coefficient obtained from the estimation of the the matching-DID model for various employment-related measures, for Italy. We only focus on micro and small firms. The vertical bars represent 95% asymptotic confidence intervals. Regressions include fixed effects and controls as from Equation 3.2.

due to employment protection policies implemented by both Member States during this period, such as restrictions on dismissals and leave schemes, with national social security systems covering employee wages. This is also clearly illustrated by the findings reported in the upper right-hand part of the figure, which show the impact of the aid on employee costs (i.e. the amount paid by firms for wages). In 2020, while the number of employees of the beneficiaries remained unchanged, the cost of employees decreased by 4% and 3% in the two countries. In 2022, the number of employees of Covid-Aid beneficiaries increased by about 2% and 4% in Spain and Italy respectively compared to non-beneficiaries. The cost of employees did not change in Spain but increased by 4% in Italy.

As employment remained relatively fixed in the short term due to the adoption of widespread furlough schemes, we use two different measures of labour productivity to assess firms' performance during the pandemic. The first measure is the ratio of sales to the number of employees, which is similar to the approach used by Konings et al. (2023) who used sales/FTE. This measure provides an indication of output per employee and is a widely used measure of productivity in the literature. The second measure, which we believe is more appropriate for our analysis, is the ratio of turnover to employee costs. This measure captures the total expenditure on labour, reflecting the true cost of employment to the firm during the pandemic. It is particularly relevant in the context of

the Covid-19 crisis. As the furloughed workers were temporarily not paid by the firm, the employment costs more accurately reflect the labour force actively engaged in production during the closure, providing a more accurate measure of labour productivity during this period.

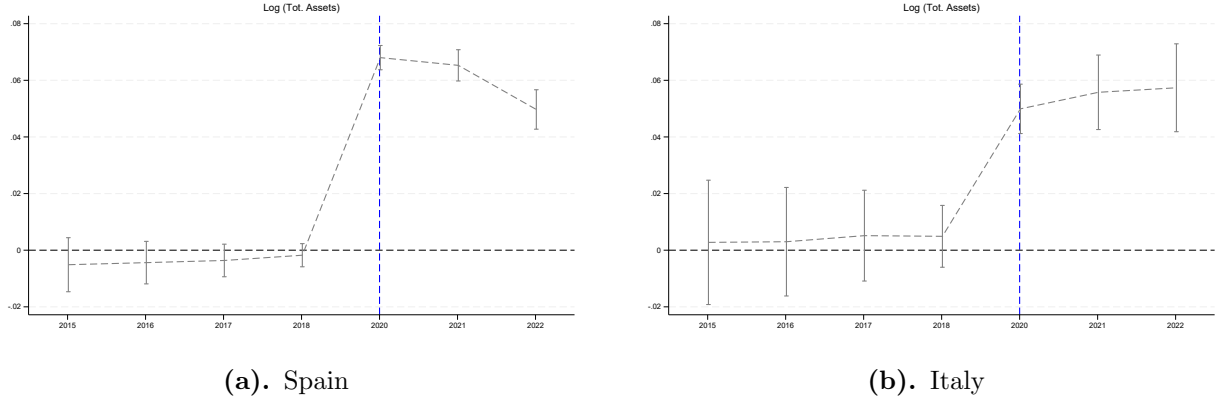
While the first measure estimate a 4% drop in firms' productivity in 2020, with a slow recovery to pre-pandemic levels by 2022, the second variable indicates only a smaller decrease in Spain in 2020, with a quicker recovery to pre-pandemic levels compared to non-beneficiaries. This suggests that government support was effective in maintaining productivity over time for firms receiving aid but did not have longer term effects.

4.2.2 Investment

While the primary objective of the aid was to support firms in maintaining production during the crisis, it is also important to assess how firms used this financial aid. In particular, we focus on total assets to assess the impact of COVID-19 aid on investment, as investments are defined as the year-over-year change in total assets.

Figure 5 shows that Covid-Aid increased firms' total assets relative to non-beneficiaries by 7.1% in 2020 and 5.4% in 2022 in Spain, and by an annual rate of 5% in Italy.

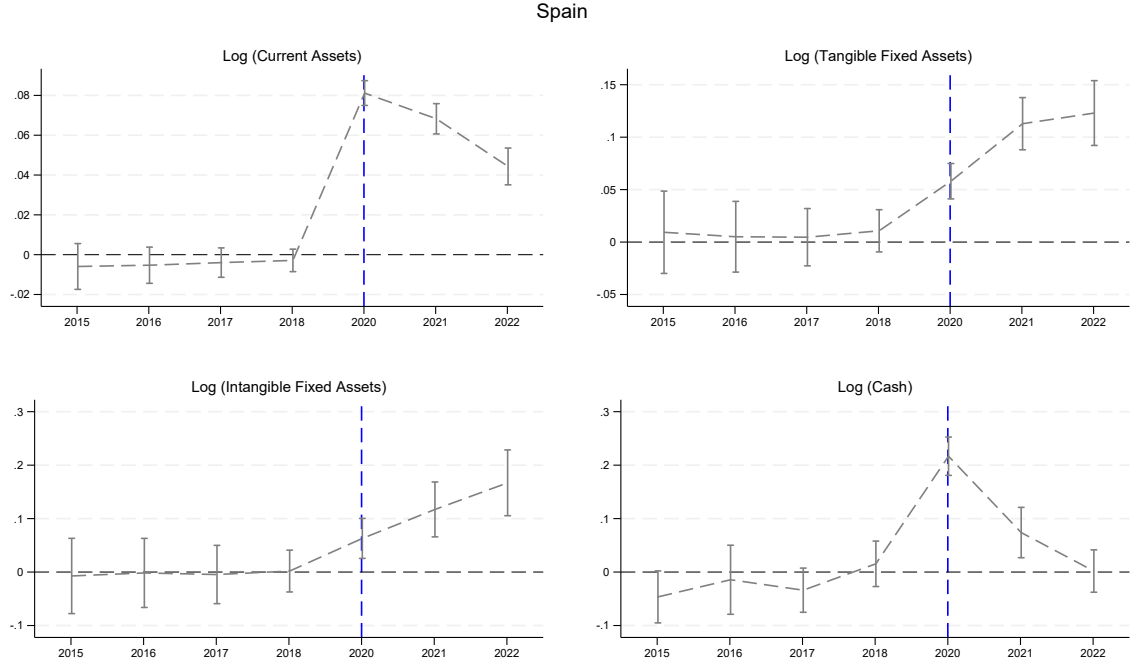
Figure 5: The effect of receiving Covid-Aid on firms' total assets



Notes: Each panel displays on the y-axis the coefficient obtained from the estimation of the matching-DID model for total assets. We only focus on micro and small firms. The vertical bars represent 95% asymptotic confidence intervals. Regressions include fixed effects and controls as from Equation 3.2.

At the same time, changes in total assets do not fully capture firms' investment behavior, as total assets are made up of two components: fixed and current assets. When aid is transferred to a firm, the corresponding cash inflow is recorded under current assets – specifically in the 'cash' account, which includes liquidity held on hand or in bank accounts. As a result, receiving aid can lead to a mechanical increase in total assets without indicating higher investment, which would instead be reflected in the accumulation of fixed assets. To disentangle these effects, we estimate our model separately for four

Figure 6: The effect of receiving Covid-Aid on the various components of total assets - Spain



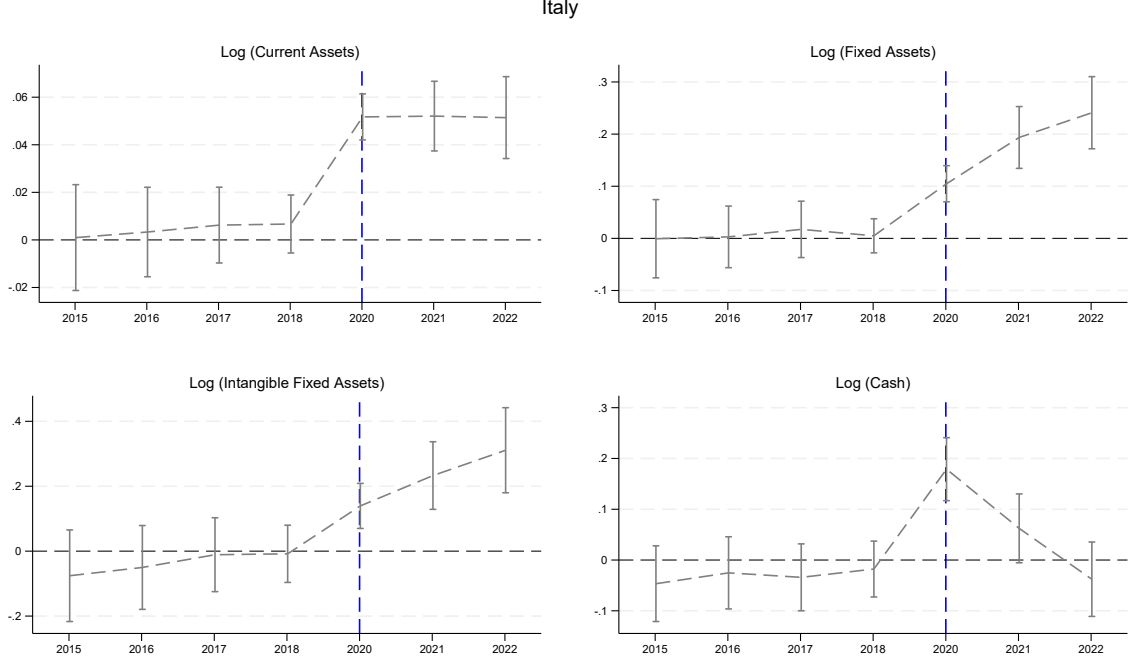
Notes: Each panel displays on the y-axis the coefficient obtained from the estimation of the the matching-DID model for the different components of total assets, for Spain. We only focus on micro and small firms. The vertical bars represent 95% asymptotic confidence intervals. Regressions include fixed effects and controls as from Equation 3.2.

sub-components of total assets: fixed tangible and intangible assets, current assets, and cash.¹⁷ The results are presented in Figures 6 and 7.

In both countries, the cash component peaked in 2020 and gradually declined to zero by 2022. Notably, the aid resulted in a sustained increase in both tangible and intangible fixed assets from 2020 onward, indicating a significant shift in firms' investment. This may have contributed to the stronger turnover performance observed among COVID aid beneficiaries in subsequent years. Interestingly, in both Italy and Spain, the increase in intangible assets outpaced that of tangible assets. Intangible fixed assets include items such as patents, trademarks, and software licenses that firms acquire for long-term use. This trend suggests that firms may have strengthened their digital capabilities either to adapt to evolving business needs -such as expanding e-commerce activities- or to digitalise internal processes in order to enhance resilience and ensure continuity (e.g. Harasztosi et al., 2022). Importantly, these investments in digital technologies may generate long-lasting benefits, potentially transforming firms' operational models beyond the crisis period.

¹⁷Fixed tangible and intangible assets represent physical and non-physical resources that provide long-term value, while current assets—including cash—are short-term assets expected to be converted into cash, sold, or consumed within one year.

Figure 7: The effect of receiving Covid-Aid on the various components of total asset - Italy



Notes: Each panel displays on the y-axis the coefficients obtained from the estimation of the matching-DID model for the different components of total assets, for Italy. We only focus on micro and small firms. The vertical bars represent 95% asymptotic confidence intervals. Regressions include fixed effects and controls as from Equation 3.2.

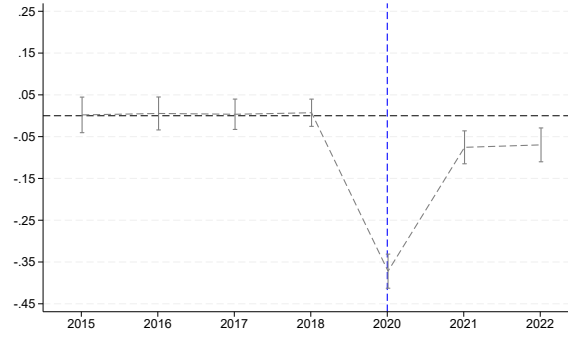
4.2.3 Profitability

Lastly, we analyse the impact of receiving Covid aid on firms' profitability, an additional indicator of firm performance. Profitability is measured using the EBIT margin, defined as the ratio of EBIT (Earnings Before Interest and Tax) to sales, where EBIT is calculated as:

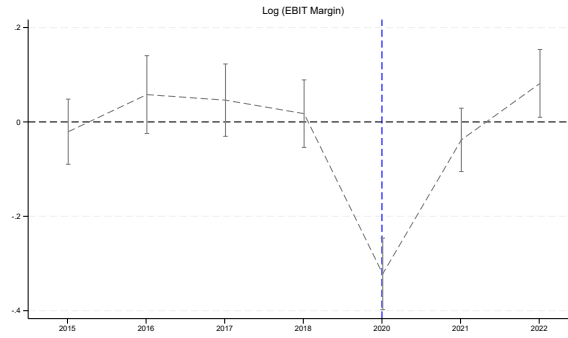
$$EBIT_{it} = Turnover_{it} - (Raw\ Material\ Costs_{it} + Services\ Costs_{it}) - (Personnel\ Cost_{it} + Other\ Operating\ Costs_{it}) \quad (2)$$

Figure 8 shows that, in both countries, profitability follows a similar pattern to that of turnover: a sharp decline in 2020, followed by a slow recovery towards pre-pandemic levels in the following years. This is not surprising, as turnover is a key component in the computation of EBIT. Nonetheless, it is important to note that the decline in EBIT margin would have been more pronounced without the support provided by wage subsidies, which effectively reduced personnel costs (see Equation 2).

Figure 8: The effect of receiving Covid-Aid on profitability



(a). Spain



(b). Italy

Notes: Each panel displays on the y-axis the coefficients obtained from the estimation of the matching-DiD model for employment. We only focus on micro and small firms. The vertical bars represent 95% asymptotic confidence intervals. Regressions include fixed effects and controls as from Equation 3.2.

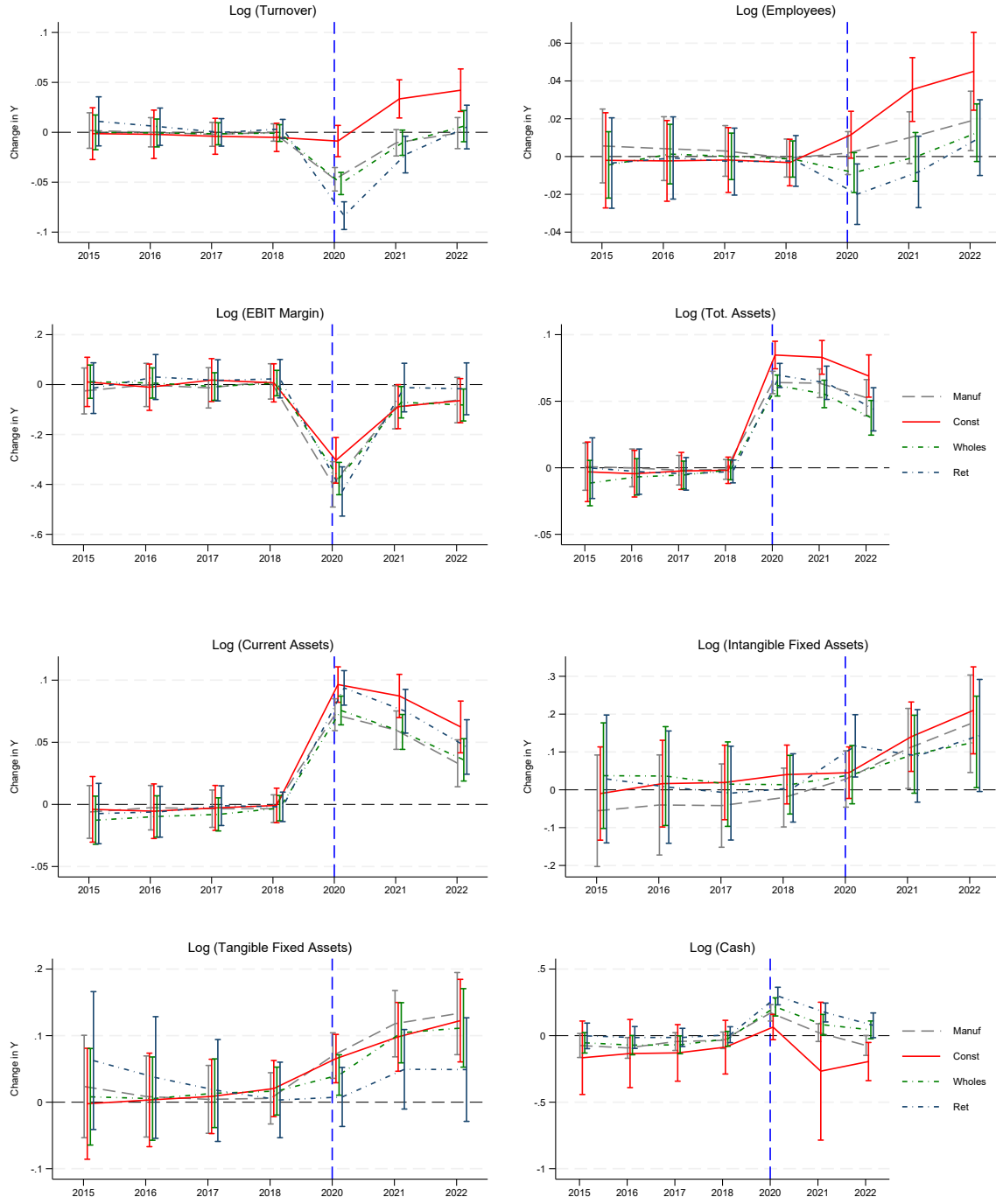
5 Extensions

5.1 Exploring Heterogeneity by Sector

The Covid-19 pandemic affected different sectors of the economy in markedly different ways. While some sectors were severely disrupted, others were relatively less affected, leading to heterogeneous patterns in the uptake and potential effects of Covid-Aid. This section examines whether the impact of aid varied across sectors. As noted earlier, the analysis focuses exclusively on micro and small firms, excluding larger firms due to the lack of statistically significant results in that group.

The construction sector appears to have played a key role showing a significant overall increase in firms' turnover as well as a relevant growth in total assets and employment in both Spain and Italy as showed in Figures 9 and 10, respectively. However, while Spain exhibited a consistent investment behaviour across sectors, in Italy firms in the wholesale sector showed a statistically significant positive but declining effect over time. To better

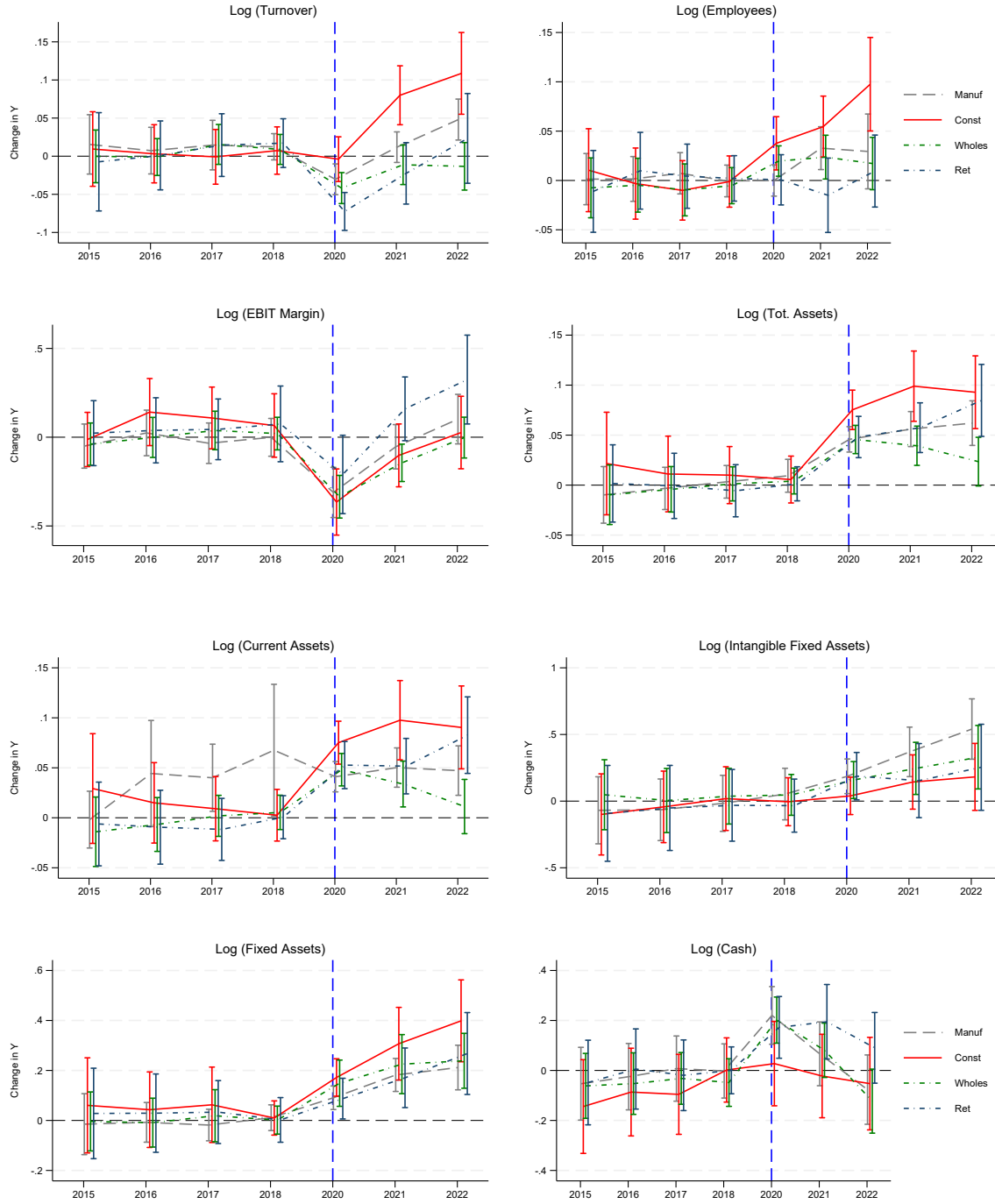
Figure 9: The effect of receiving Covid-Aid on various measures of firm performance, by industry sector - Spain



Notes: Each panel displays on the y-axis the coefficients obtained from the estimation of the matching-DiD estimator for different measures of firms' performance, namely turnover, employment, EBIT margin, total assets, as well as their different components. We only focus on micro and small firms. The vertical bars represent 95% asymptotic confidence intervals. Regressions include fixed effects and controls as from Equation 3.2.

understand what happened within the construction sector and its investment dynamics,

Figure 10: The effect of receiving Covid-Aid on various measures of firm performance, by industry sector - Italy



Notes: Each panel displays on the y-axis the coefficients obtained from the estimation of the matching-DiD estimator for different measures of firms' performance, namely turnover, employment, EBIT margin, total assets, as well as their different components. We only focus on micro and small firms. The vertical bars represent 95% asymptotic confidence intervals. Regressions include fixed effects and controls as from Equation 3.2.

we further disaggregate and analyse total assets into its sub-components. In Spain, this

additional breakdown does not provide any significant insights. For Italy, however, the results reveal interesting patterns. Small firms in the construction sector used Covid Aid to increase their fixed tangible assets. By 2020, their endowment was 20% higher than in the pre-treatment period and compared to non-beneficiaries; this increase doubled in two years and was larger than in other sectors. In contrast, small manufacturing firms in Italy experienced a much larger increase (50%) in intangible fixed assets than other sectors.

These results suggest that firms in the two countries adopted a variety of strategies to cope with the crisis with the support of Covid-Aid. In Spain, for example, the retail sector did not increase investment in tangible assets significantly as the Italian did. One possible explanation is that Italian firms used the funds to renovate or upgrade physical premises, while Spanish firms may have prioritised intangible investments, such as the digitalization of internal processes. Notably, firms in Spain’s construction sector exhibit positive and statistically significant effects for both tangible and intangible assets, whereas in Italy the effect is statistically significant only for tangible assets. This divergence may reflect Spain’s growing emphasis on digitalization and technology adoption within the construction sector, aimed at enhancing worker safety and productivity, as noted by several analysts.^{footnote}See McKinsey (2020) (available online).

5.2 Heterogeneity in Treatment over Time

We exploit some of the peculiarities of the TF design to understand how specific aspects of the aid scheme or its delivery mechanism might influence the impact of State Aid on firms during a crisis. First, we assess the effect of multiple treatments by comparing the results between firms that received aid only in 2020 and those that received aid in both 2020 and 2021. Next, we examine the extension of aid coverage by analysing the impact of aid disbursed in 2021, during which the take-up of aid by larger firms increased.

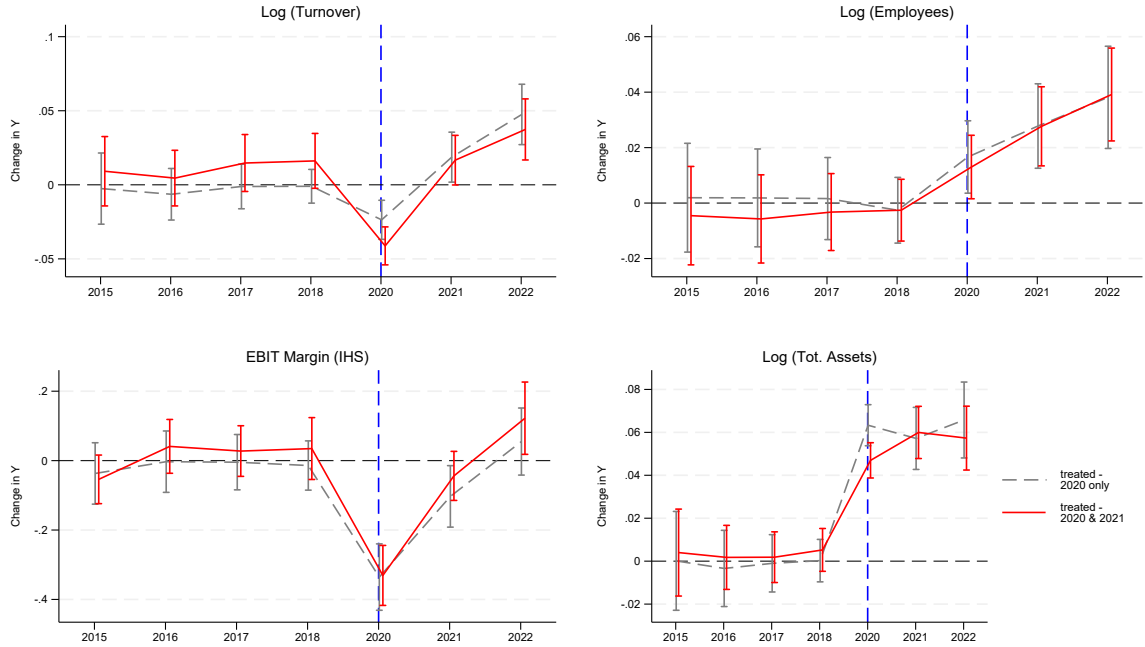
5.2.1 Multiple Rounds of Treatment

During the pandemic crisis, firms could have received aid multiple times, as financial assistance was subject to specific aid caps defined over a set period, according to the TF. For example, *de minimis* aid was granted over a three-year period with a maximum limit of €200,000. Consequently, some firms received aid only in 2020, while others benefited multiple times by reapplying for funding or receiving aid in instalments. In our sample, Spanish and Italian firms received support an average of 1.3 and 1.6 times, respectively. In Spain, most firms received financial aid early in the pandemic, while in Italy, aid

distribution occurred later.¹⁸ Among Spanish beneficiaries, 86% received support by the end of 2020. In contrast, in Italy, 51.3% of Covid Aid recipients were supported in 2021 or 2022.¹⁹

To this end, we re-estimate our baseline model using a newly defined treatment variable that captures firms with repeated treatment in both 2020 and 2021, and compare the results with those obtained when the treatment variable identifies firms that received aid only once.²⁰ The results, shown in Figure 11 indicate that multiple treatments yield similar results, suggesting no multiplicative effects on the outcomes considered. However, a limitation of this analysis is that it does not account for the amount of aid received by each firm, due to data unavailability.

Figure 11: The effect of receiving Covid-Aid on firm performance, by treatment year - Italy



Notes: Each panel displays on the y-axis the coefficients obtained from the estimation of the matching-DiD model for the different measures of firms' performance, comparing firms that received aid only in 2020 with those that received aid in both 2020 and 2021 represent 95% asymptotic confidence intervals.

¹⁸The reason for this discrepancy in the timing of aid distribution is unclear and may be tied to differing political strategies. Canzian et al. (2024) found that Spain made substantial use of *de minimis* aid (approximately 50%), which has lower caps and faster procedures. In contrast, Italy's use of *de minimis* aid was limited (less than 5%).

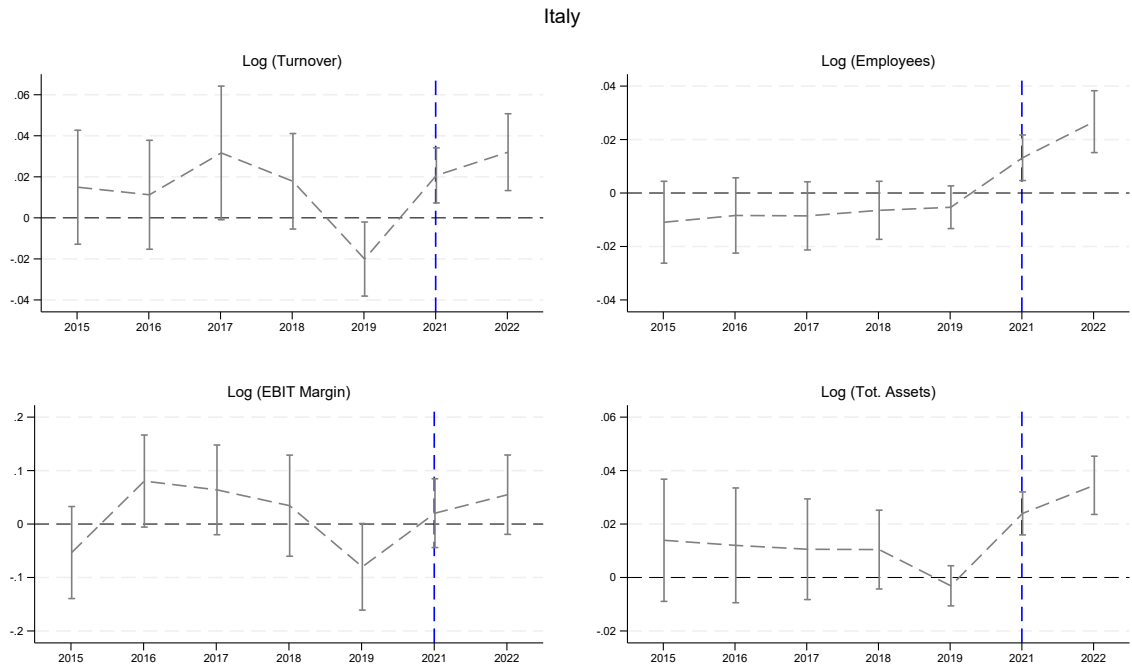
¹⁹These figures are based on the balanced panel, but are similar to those observed in the unbalanced sample.

²⁰We only perform this analysis for Italy, as the number of firms receiving multiple treatments in Spain is too small.

5.2.2 Broadening of the Aid Scope

The TF measures remained in force until the end of 2023, although they were initially designed as temporary instruments to help firms cope with the crisis. In Italy, around 38.5% of beneficiaries received aid under the Sixth Amendment (in the fourth quarter of 2021 or later). Furthermore, the share of firms that did not receive aid over the entire period was 53.3% in Spain, compared to only 20.6% in Italy. The descriptive evidence provided in Table 1 highlights differences between firms that received aid in different waves.

Figure 12: The effect of receiving Covid-Aid on firm performance for firms treated in 2021 - Italy



Notes: Each panel displays on the y-axis the coefficients obtained from the estimation of the matching-DiD model for different measures of firms' performance for firms treated in 2021. The vertical bars represent 95% asymptotic confidence intervals.

In this section, we focus on the sample of Italian firms that first received Covid Aid in 2021, to test whether broader coverage –both in terms of scope and recipient profile, as the aid increasingly targeted medium-to-large firms– produced comparable effects on firm performance. The control group consists of firms that were never treated at any point during the 2015-2022 period.²¹ However, the results shown in Figure 12 should be interpreted with caution. This identification strategy raises additional concerns related to endogeneity –such as potential anticipation effects and the self-selection of larger or more

²¹In these models, the pre-treatment period spans from 2015 to 2020, and the matching method accounts for covariates observed within this period.

productive firms into treatment— particularly given the delayed nature of the financial support. Having these concerns in mind, our estimates suggest that receiving Covid aid in 2021 is positively associated with increases in turnover, investment, and employment as measured in 2022.

When disaggregating the effects by size class and sector, we find that the positive association with turnover is statistically significant only for micro-firms and in the manufacturing and construction. A broadly positive effect on employment is observed across all sectors and firm sizes. For medium-to-large firms, we find a positive association with investment.²²

5.3 Firms’ exit from Orbis

The results presented so far are based on a balanced panel of firms observed continuously over the period 2015–2022. This approach enables us to examine within-firm performance over time, focusing specifically on firms that survived throughout the pandemic. It also allows for precise control over firms’ financial characteristics during the entire pre-treatment period, thereby improving the comparability between aid recipients and non-recipients by aligning their eligibility conditions—and, consequently, their likelihood of receiving aid. However, focusing exclusively on a balanced sample raises concerns about potential sample selection bias, particularly regarding the effect of aid on post-treatment survival. To address this issue, we examine whether the probability of exiting the sample differs systematically between beneficiaries and non-beneficiaries, thereby assessing the possible magnitude of such a bias.

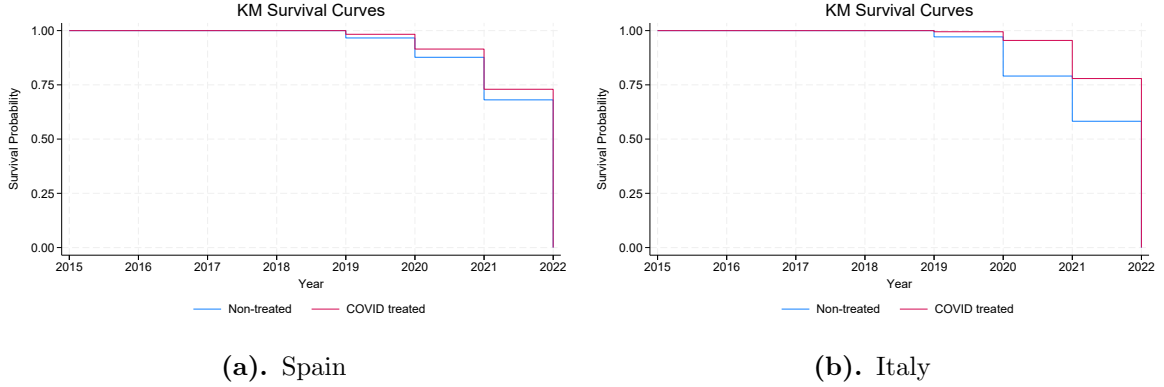
Given the well-known limitations of the Orbis database, however, it is important to note that the observed differences in survival between the two groups may be driven by two different mechanisms. First, aid may have directly influenced the likelihood of firms actually exiting the market after 2019. Second, there may be differences in reporting behaviour or legal reporting obligations between beneficiaries and non-beneficiaries that affect whether firms are still observed in the data in later years. The latter mechanism is particularly relevant as reporting behaviour may be associated with unobservable characteristics—such as management quality or administrative efficiency—that may also be correlated with the likelihood of receiving aid.

For this analysis, we focus on the sample of firms observed over the entire pre-treatment (2015–2019) period, but which may or may not exit the sample after 2019. Figure 13 presents survival curves for beneficiaries and non-beneficiaries in Spain and Italy. In Spain, there is relatively little difference between the two groups, while in Italy

²²Results by size and sector are not shown and are available upon request.

the survival rate of beneficiaries is significantly higher than that of non-beneficiaries.

Figure 13: Kaplan-Meier Survival Curves by Covid Benefit Status: firms alive between 2015 and 2019



To better understand these differences, we estimate Cox proportional hazard models to compare the probabilities of firms exiting the Orbis dataset between Covid Aid beneficiaries and non-beneficiaries, after accounting for pre-treatment covariates using PSM. The results are presented in Table 3. We use two model specifications: one with pre-treatment covariates and one without, and we repeat the analysis for the subset of firms observed between 2015 and 2020 to further test robustness. In Spain, firms that received Covid Aid had 8.5% lower hazard of exiting the Orbis database compared to non-beneficiaries, while in Italy, this figure is 22.3%. These differences are smaller when controlling for pre-treatment firm characteristics using PSM, with hazard ratios reduced to 5.7% for Spain and 21.2% for Italy.

One possible interpretation of these results is that Covid Aid may have had a protective effect on firms, particularly in Italy, reducing their risk of market exit. However, differences in survival rates should have been substantially mitigated by temporary policies implemented by many European governments –including Italy and Spain– that suspended insolvency and bankruptcy proceedings in the years following the pandemic. Alternatively, such differences may be due to variations in reporting procedures, as explained above. If this was the case, selecting a balanced sample of firms would provide an indirect way to control for unobservable differences that correlates with reporting behaviours. Therefore, selecting a balanced sample may enhance the robustness of the proposed identification strategy.

Table 3: Firms’ Exit and Covid-19 aid: Hazard Ratios from Cox Proportional Hazard models, comparing Covid beneficiaries and non-beneficiaries

Spain				
Sample	firms alive between 2015 and 2019		firms alive between 2015 and 2020	
Received Covid Aid	0.915*** (0.005)	0.943*** (0.003)	0.939*** (0.006)	0.958*** (0.003)
PS Matching	No	Yes	No	Yes
Observations	726,477	726,477	713,392	713,392
Italy				
Sample	firms alive between 2015 and 2019		firms alive between 2015 and 2020	
Received Covid Aid	0.777*** (0.007)	0.788*** (0.007)	0.797*** (0.007)	0.804*** (0.005)
PS Matching	No	Yes	No	Yes
Observations	424,602	424,602	421,544	421,544

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Hazard Ratio (HR)
Interpretation: $HR = 1$ implies equal hazard for beneficiaries and non-beneficiaries. $HR < 1$ indicates lower hazard for beneficiaries. $HR > 1$ indicates higher hazard for beneficiaries.

6 Conclusions

The Covid-19 pandemic was an unprecedented economic shock that forced governments to take swift action to stabilise economies and prevent systemic collapse. This paper examines how State Aid, structured under the European Union’s Temporary Framework, affected the performance of firms during and after the crisis. Focusing on two severely affected Member States, Italy and Spain, the analysis assesses the effectiveness of these interventions by considering their impact on firm performance indicators such as turnover, investment and employment.

The study employs a micro-econometric approach, combining a difference-in-differences (DiD) methodology with propensity score matching (PSM) and alternative estimation strategies to enhance the robustness of the findings. The results underline that the TF was effective in supporting micro and small firms through the crisis. Micro firms, in particular, experienced the most pronounced recovery, with significant improvements in turnover compared to non-beneficiaries. In contrast, no significant effects were observed for medium and large firms, which were less targeted by the TF.

In both countries, aid not only contributed to the stabilisation of micro and small firms, but also produced unexpected positive effects on investment –particularly in intangible assets– which may foster dynamic competitive advantages over the longer term. While such outcomes could suggest a distortion of competition, the evidence indicates

that any such effects were likely limited. Although the analysis does not directly measure competition outcomes, several factors point to a low risk of significant distortion: most aid was directed toward micro and small firms; support was not extended to firms already in financial distress prior to the crisis; and larger firms that received aid did not significantly outperform comparable non-recipients. Moreover, even if some degree of distortion did occur, its overall market impact is likely to have been modest, as the benefits were concentrated among micro firms that generally possess limited market power.

The implications of our findings for the overall assessment of the TF are broadly positive: it proved to be an effective and timely tool to address the economic upheaval caused by the pandemic, particularly in its emphasis on supporting micro and small firms. This targeted design underlines the EU’s capacity to respond to crises within the boundaries of existing State Aid control mechanisms, striking a balance between flexibility and economic stability. However, caution is warranted. The diminishing returns observed in successive TF extensions highlight the potential risks associated with over-reliance on such frameworks. As the scope of the aid was gradually broadened—allowing greater access for larger firms, including through measures supporting green investments—the benefits became more limited, while the risk of market distortions increased. This underscores the importance of keeping temporary aid frameworks narrowly targeted and time-bound to maintain their effectiveness. This consideration is particularly relevant, as the incoming European Commission, taking office in 2025, has proposed to extend aid for climate-friendly investments under a simplified procedure until 2030. To enable this, the current Temporary Crisis and Transition Framework is expected to be extended.

While this study contributes novel empirical evidence to the growing literature on the evaluation of Covid State Aid –and more broadly, on the role of government financial support in times of crisis– several challenges remain. Future research would greatly benefit from improved data quality and access, especially for cross-country comparisons. The TAM database, which is intended to be a central resource for tracking aid beneficiaries in the EU, lacks the completeness and granularity of national registers, making identification of causal effects even more challenging. Moreover, administrative data on firm characteristics could substantially enhance the depth of analysis and provide a more comprehensive perspective than is currently possible with Orbis, which remains limited in both coverage and detail. In addition, while our study provides micro-level insights into the direct impact on aid recipients, it does not account for general equilibrium effects, spillovers, or broader market dynamics. A more structural approach –incorporating sectoral and regional interdependencies– could offer deeper insights into these broader effects.

Future research could also explore treatment intensity, assessing whether varying levels of aid –as opposed to a binary distinction between beneficiaries and non-beneficiaries–

affected firm outcomes. Although the Temporary Framework was designed to allocate aid proportionally to the minimum amount needed, largely based on firm size, further analysis could clarify whether larger amounts of aid produced stronger recovery effects, or whether diminishing returns emerged beyond a certain threshold. Such extensions would contribute to a more nuanced understanding of the long-term economic consequences of crisis-driven state support.

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A Appendices

A.1 Temporary Framework

Exclusion criteria

The TF's withholds support from firms that were in difficulty before December 31, 2019. The conditions under which a company is considered in difficulty according to the Commission Regulation (EU) No 651/2014 can be summarised as follows:

- (a) For a limited liability company (except for young SMEs and certain SMEs eligible for risk finance aid), it is considered in difficulty if accumulated losses have reduced its net assets to less than half of its subscribed share capital.
- (b) For companies with members having unlimited liability for the company's debt (again, except for young SMEs and certain SMEs eligible for risk finance aid), the company is in difficulty if accumulated losses amount to more than half of the capital shown in the company accounts.
- (c) A company is in difficulty if it is undergoing collective insolvency proceedings or meets the national criteria to be placed in such proceedings by creditors.
- (d) If a company has received rescue aid but has not yet repaid the loan or ended the guarantee, or has received restructuring aid and is still under a restructuring plan, it is considered in difficulty.
- (e) A non-SME company is in difficulty if, for the past two years, it has had a book debt-to-equity ratio greater than 7.5 and an EBITDA interest coverage ratio below 1.0.

Amendments to the Temporary Framework

The TF, initially established to provide support during economic disruptions, underwent several amendments to address the evolving needs of businesses during the period in question.²³ These amendments expanded the types of financial assistance available and adjusted eligibility criteria to ensure aid reached companies most in need. We summarise the key features of such amendments that may be relevant for the present analysis as follows:

²³For an overview of these amendments, please visit https://competition-policy.ec.europa.eu/state-aid/coronavirus/temporary-framework/amendments_en

Amendments 1-3 (2020, quarter 2)

These measures aimed to provide immediate liquidity support and offer a lifeline to companies struggling with solvency issues:

- *Amendment 1*: broadened the spectrum of financial instruments, including zero-interest loans, guarantees with full risk coverage, and provisions for equity investments.
- *Amendment 2*: allowed for enhanced support through measures such as recapitalization and the issuance of subordinated debt
- *Amendment 3*: offered incentives for private investors to participate in the recapitalization efforts of affected firms.

Amendments 4-5 (2020, quarter 4)

As the pandemic progressed, the need for more targeted support became evident. Hence, two additional amendments were approved:

- *Amendment 4*:
 - Set additional eligibility criteria, specifically targeting companies that experienced a sharp decline in turnover-defined as a 30% drop compared to the previous year.
 - Supported uncovered fixed costs and increased the existing aid caps, thereby offering more substantial financial relief to those businesses most impacted.
- *Amendment 5*: introduced the possibility for Member States to convert repayable instruments into direct grants.

Amendment 6 (2021, quarter 4)

By the end of 2021, with the introduction of the *Amendment 6*, the focus of the Temporary Framework shifted towards fostering a resilient and sustainable recovery. This latest amendment incorporated two new measures: one that provided incentives for investments in the green and digital transition, ensuring that the recovery path aligned with long-term environmental and digital objectives; and another that introduced support measures, such as guarantees to private intermediaries, to catalyse private funding for SMEs, thereby enhancing their access to essential capital resources.

A.2 Sample selection

Data Cleaning	ES	IT
Total starting no. of observations (2015-2022)	6,334,134	16,769,140
Orbis — cleaning		
Remove bad-coverage sectors (agriculture and fishery, PA, Finance and Insurance)	378,424	1,823,110
Consolidated accounts (Code C2)	9,186	14,316
Duplicates	-	60
Coding errors and incomplete data		
No. employees <0 OR no. employees >2 million	1,757,968	3,730,250
Turnover or sales <0	1	4,522
Tangible fixed assets or total assets <0	14,736	-
Both turnover AND other operating expenses missing	-	1,002,341
<i>Remaining observations</i>	<i>4,173,819</i>	<i>10,194,541</i>
Sample Selection		
Sectors not suitable for analysis due to sample size	2,998,745	3,998,361
Beneficiaries of Non-Covid State aid	642,709	1,946,677
Year =2013	6	108
<i>Remaining observations</i>	<i>2,281,277</i>	<i>4,249,395</i>
Missing values		
Size	-	577,030
Other financial variables	655,645	2,717,390
<i>Remaining observations</i>		
Unbalanced panel	1,403,330	954,975
Balanced panel	483,488	348,528

Notes: The table outlines the cleaning steps that led to the final sample.

Table A1: Firms characteristics of analysed samples compared to excluded observations

Panel A - Spain								
Firm characteristics	Analysed sample		Excluded observations		Diff.	p-value	N analysed sample	N excluded observations
	%		%					
Micro	87%		97%		-0.100	0.000	190,700	94,186
Small	10%		3%		0.070	0.000	190,700	94,186
Medium	2%		0%		0.020	0.000	190,700	94,186
Large	1%		0%		0.010	0.000	190,700	94,186
Construction	27%		44%		-0.160	0.000	190,700	94,186
Manufacturing	22%		12%		0.100	0.000	190,700	94,186
Wholesale	30%		29%		0.010	0.000	190,700	94,186
Retail	21%		15%		0.050	0.000	190,700	94,186
	Mean	SD	Mean	SD	Diff.	p-value		
No. Employees	9.53	76.09	3.45	14.13	6.070	0.000	190,700	24,268
Turnover (€M)	2.80	63.35	0.50	9.52	2.300	0.000	190,700	78,945
EBIT margin	1.70	15.22	9.85	32.67	-8.150	0.000	190,700	67,068
Total Assets (€M)	2.18	47.84	2.31	106.56	-0.120	0.671	190,700	94,186
Cost of Materials (€M)	1.98	48.87	0.45	9.15	1.540	0.000	190,700	53,867
Capital (€M)	0.22	6.19	0.46	17.73	-0.240	0.000	190,700	94,178
Fixed Assets (€M)	0.82	26.02	1.37	96.77	-0.540	0.022	190,700	94,186
Current Assets (€M)	0.00	0.00	0.00	0.00	0.000	0.000	190,700	94,186
Loans (€M)	0.12	3.02	0.09	4.76	0.030	0.037	190,700	87,325
Panel B - Italy								
Firm characteristics	Analysed sample		Excluded observations		Diff.	p-value	N analysed sample	N excluded observations
	%		%					
Micro	87%		100%		-0.130	0.000	124,086	686,914
Small	10%		0%		0.100	0.000	124,086	686,914
Medium	2%		0%		0.020	0.000	124,086	686,914
Large	1%		0%		0.010	0.000	124,086	686,914
Construction	28%		28%		0.000	0.005	124,086	686,914
Manufacturing	26%		13%		0.120	0.000	124,086	686,914
Wholesale	27%		23%		0.030	0.000	124,086	686,914
Retail	20%		35%		-0.160	0.000	124,086	686,914
	Mean	SD	Mean	SD	Diff.	p-value		
No. Employees	7.56	64.91	1.41	2.09	6.150	0.000	124,086	686,914
Turnover (€M)	3.41	127.78	0.25	0.83	3.160	0.000	124,086	686,914
EBIT margin	3.55	17.11	8.85	30.52	-5.300	0.000	124,086	3,147
Total Assets (€M)	2.76	61.26	3.75	44.37	-0.990	0.180	124,086	7,083
Cost of Materials (€M)	2.29	110.16	0.18	1.64	2.110	0.286	124,086	3,097
Capital (€M)	0.18	6.98	0.11	3.78	0.070	0.000	124,086	221,045
Fixed Assets (€M)	0.82	28.00	1.99	30.37	-1.170	0.001	124,086	7,083
Current Assets (€M)	0.00	0.00	0.00	0.00	0.000	0.756	124,086	7,083
Loans (€M)	0.17	12.82	0.31	6.21	-0.140	0.368	124,086	7,083

Table A2: Distribution of firms by beneficiary status and classes of sales' drop in 2020.

Country	Spain				Italy			
Group	Control		Treated		Control		Treated	
Variation in 2020 sales	%	N	%	N	%	N	%	N
Decrease (60-100%)	1.7%	540	2.4%	587	2.1%	189	3.2%	290
Decrease (30-60%)	11.7%	3,768	17.2%	4,178	14.2%	1,267	19.7%	1,760
Decrease (15-30%)	21.1%	6,800	23.9%	5,823	22.0%	1,969	24.7%	2,205
Decrease (0-15%)	28.9%	9,292	26.8%	6,518	28.2%	2,518	26.0%	2,321
Increase (0-20%)	23.6%	7,598	19.2%	4,674	21.2%	1,893	16.4%	1,467
Increase (20-100%)	11.4%	3,656	9.5%	2,304	10.5%	940	8.6%	768
Increase (over 100%)	1.4%	450	1.0%	242	1.8%	160	1.4%	124
Total	100%	32,183	100%	24,341	100%	8,942	100%	17,734

Notes: The table reports the percentage and number of firms in control and treated groups across different ranges of sales variation measured in 2020 for Spain and Italy. Firms are categorised into seven groups based on the extent of sales shocks: three groups of decreases (60-100%, 30-60%, and 15-30%), one group with minimal decrease (0-15%), and three groups of increases (0-20%, 20-100%, and over 100%)

Table A3: Probit models. Dependent variable = 1 if firm is not reported in a given year (see table); marginal effects. Year: 2019.

Country	ES			IT		
Outcome	Firm not appearing after 2019	Firm not appearing after 2020	Firm not appearing after 2021	Firm not appearing after 2019	Firm not appearing after 2020	Firm not appearing after 2020
COVID aid beneficiary	-0.147*** (0.002)	-0.036*** (0.002)	-0.039*** (0.003)	-0.255*** (0.003)	-0.117*** (0.002)	-0.084*** (0.004)
Construction	-0.007*** (0.002)	0.002 (0.002)	0.001 (0.004)	0.001 (0.003)	0.000 (0.003)	0.011** (0.004)
Wholesale	0.009*** (0.002)	0.007*** (0.002)	0.009** (0.004)	0.000 (0.003)	0.001 (0.003)	0.007 (0.005)
Retail	0.014*** (0.002)	0.013*** (0.003)	0.013*** (0.004)	0.018*** (0.003)	0.013*** (0.003)	0.030*** (0.005)
Log (turnover)	-0.014*** (0.001)	-0.012*** (0.002)	-0.004* (0.002)	-0.021*** (0.002)	-0.018*** (0.002)	-0.051*** (0.003)
EBIT margin	-0.002*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.002*** (0.000)
Log (tot. assets)	0.000 (0.001)	0.003** (0.001)	0.014*** (0.002)	0.003** (0.001)	0.008*** (0.001)	0.028*** (0.002)
Log (employees)	-0.006*** (0.001)	-0.004*** (0.001)	0.002 (0.002)	-0.006*** (0.001)	-0.003** (0.002)	0.003 (0.002)
Log (material costs)	-0.005*** (0.000)	-0.003*** (0.001)	-0.004*** (0.001)	-0.003*** (0.000)	-0.003*** (0.001)	-0.003*** (0.001)
Log (capital)	0.001 (0.000)	-0.002*** (0.001)	-0.000 (0.001)	-0.001** (0.001)	-0.005*** (0.001)	-0.015*** (0.001)
Loans (binary)	0.027*** (0.002)	0.005** (0.002)	-0.010*** (0.003)	0.020*** (0.002)	0.006*** (0.002)	0.006* (0.003)
Observations	124,981	114,064	103,821	74,327	65,819	60,456

Notes: Standard errors are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. Other control variables included: region. In each regression, the reference category for the dependent variable is the group of firms that had not disappeared by that specific year.

Table A4: Percentage of firms treated in each year (treated group only)

Country	ES		IT	
When first treated	N	%	N	%
2020	24,342	86%	17,734	51%
2021	3,484	12%	13,539	39%
2022	404	1%	3,301	10%
Observations	28,230	100%	34,574	100%

A.3 Methodological Appendix

A.3.1 Propensity Score Matching

Propensity scores are computed implementing the following probit model:

$$Pr(\text{Treat}_i = 1|Z_i) = \phi(\alpha_i + \beta_i Z_i) \quad (3)$$

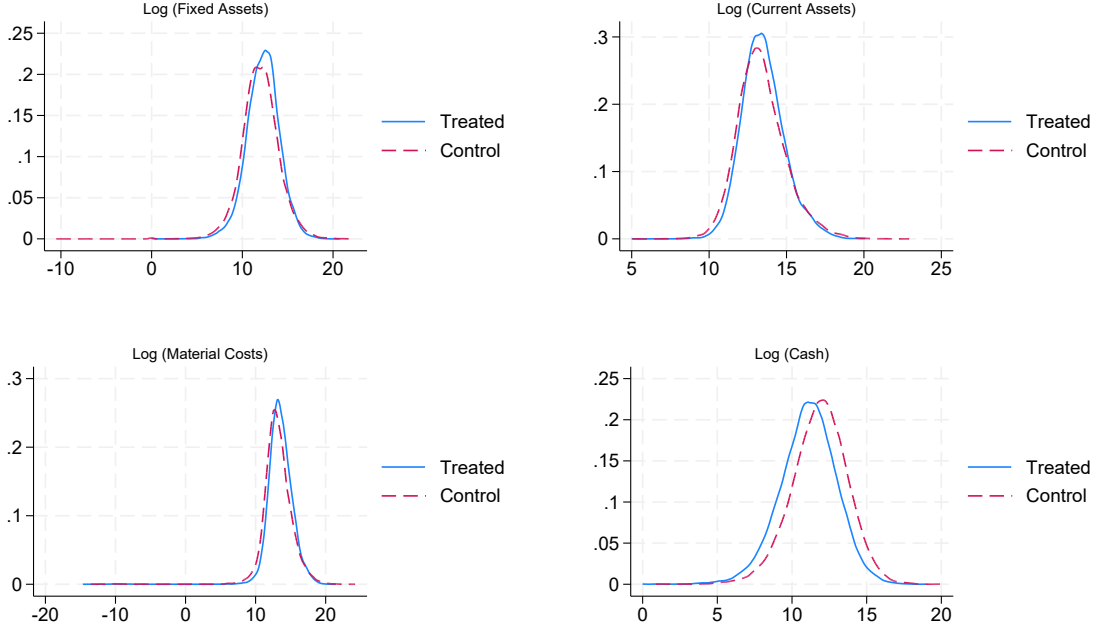
where $\phi(\cdot)$ is the cumulative standard normal distribution function; Treat_i is a binary variable = 1 if firm i received aid; Z_i is a set of firms' pre-pandemic characteristics and selected interaction terms; α_i is a constant and β_i captures the relationship between the probability of treatment and the covariates of interest. Z_i includes the following set of firm characteristics: industry sector (manufacturing, construction, wholesale and retail), firm size (micro, small, medium, large), EBIT margin, capital, fixed and current assets, and loans. These variables are important characteristics of the firms which might differ across treated and control firms. In addition, we include the firm's region (using the NUTS-2 classification) to account for geographical differences. All the covariates included in the propensity score estimation refer to the pre-treatment period to avoid any spurious correlation with the effect of the aid, which was received in 2020.

Finally, to further corroborate the parallel trend hypothesis we include pre-treatment outcomes (e.g. 2019 turnover, 2018 turnover, etc.) in Z_i to adjust for the firms' performance history prior to the pandemic. This is in line with existing literature (Heckman et al., 1997); Ryan (2018); Roth et al. (2023) and we discuss the implications of our choice on final results in Appendix A.4.

Quality of matching Ensuring covariates balancing and common support (overlap in the distribution of the covariates and propensity score distributions between the treated and untreated firms) are essential for reducing bias and making valid inference. Before implementing the matching, we analysed the distribution of selected firms' characteristics between treated and untreated firms (Figure A1 and A2). The graphs show an imperfect overlap in the distributions, especially for the tails (extreme values) of fixed assets, current assets, material costs, and cash levels between treated and controls. These differences may negatively affect the quality of the matching by challenging the common support condition. To test this we implement the matching procedure both by including and excluding these extreme values. Removing these outliers improves the covariates balancing measured as the ratio between the variance of treated and untreated firms, supporting

the choice to exclude them from the analysis.²⁴

Figure A1: Distributions of different covariates by treatment status. Spain



We then apply the most appropriate propensity score matching based on pre-treatment covariates and outcomes. Continuous variables are included in logarithms (e.g., fixed assets, current assets, or material costs). Nominal variables (e.g., sector, region) or variables exhibiting skewed distributions (e.g., loans, capital) are included as categorical. Two sets of interaction terms (for Italy and Spain) are also included to ensure good balancing in the mean differences and variance ratios.

Tables A5 and A6 present the results of covariate balancing after matching. Mean differences are generally small (below 2%) and the variance ratios are close to one. For Italy, there are some differences (mostly lower than 3%) in the regional distributions of treated and control firms due to a relatively small number of non-beneficiaries in Southern regions (e.g. Region 6). To account for such small differences, we also control for region—year fixed effects in some specifications of the the econometric models. The quality of the balancing is also confirmed by the low values (≤ 0.001 for Italy and Spain) of the Pseudo-R2 - a post-matching measure of how well the covariates explain the probability of receiving treatment.²⁵

²⁴See Markoulidakis et al. (2023) for more details on how to improve the quality of the matching. Results of the balancing tests with or without outliers are available upon request.

²⁵The standardised bias is always below 3% which is also a considered good range for this parameter in most empirical application (see Caliendo and Kopeinig (2008)).

Figure A2: Distributions of different covariates by treatment status. Italy

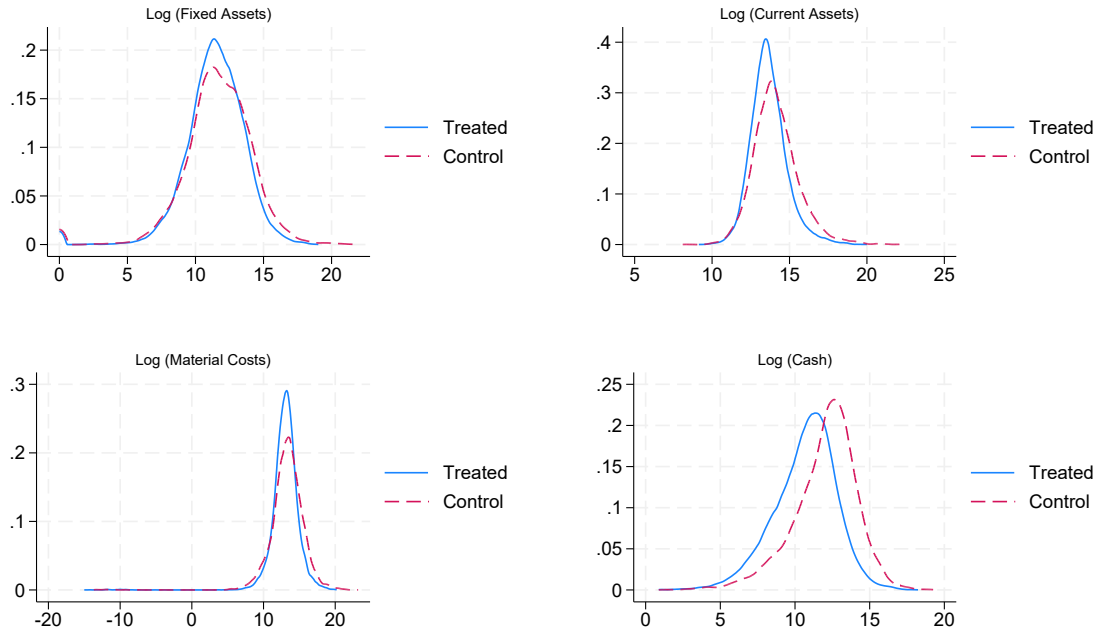


Figure A3 shows the distribution of the propensity scores. The common support condition is widely met with only a few treated companies left out of support. See Table A7.

Overall, the results suggest that the proposed matching strategy achieves good balancing by significantly reducing the differences in pre-treatment observable characteristics between treated and untreated firms.

Figure A3: Distributions of different covariates by treatment status. Spain

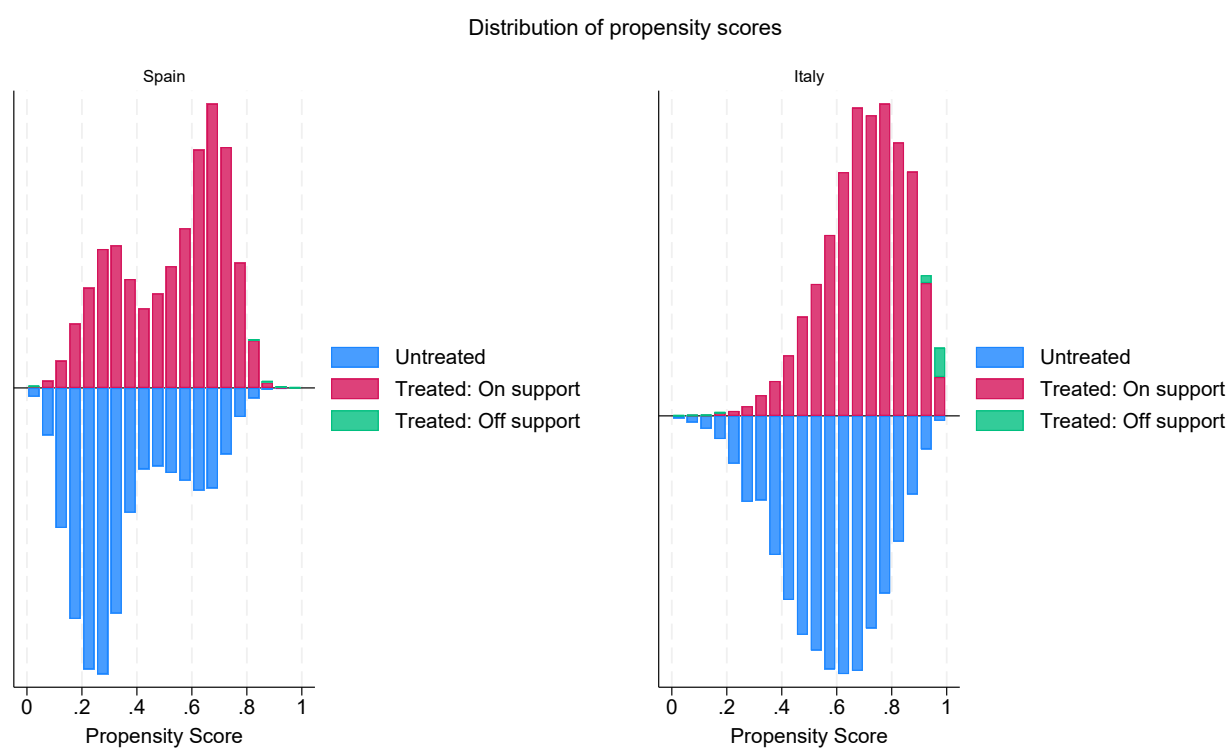


Table A5: Balancing tests of observable characteristics between treated and control. Spain

	Mean		t-test			Variance ratio
Variable	Treated	Control	%bias	t	p>t	
Continuous variables						
Turnover (2015)	14.053	14.052	0.1	0.07	0.944	0.99
Turnover (2016)	14.119	14.119	0	-0.02	0.983	0.98
Turnover (2017)	14.195	14.196	-0.1	-0.08	0.937	0.99
Turnover (2018)	14.25	14.252	-0.2	-0.18	0.86	0.99
Turnover (2019)	14.275	14.279	-0.3	-0.32	0.751	0.99
Fixed assets (log)	12.285	12.27	0.8	0.9	0.367	1
Current assets (log)	13.504	13.479	1.7	1.93	0.053	0.99
Material costs (log)	13.548	13.556	-0.4	-0.45	0.651	0.97*
Intangible fixed assets (log)	2.572	2.550	0.5	0.59	0.558	1.01
Categorical variables						
Loans (dummy)	0.672	0.673	-0.3	-0.34	0.733	
Capital (q2)	0.193	0.195	-0.6	-0.7	0.482	
Capital (q3)	0.294	0.293	0.2	0.27	0.79	
Capital (q4)	0.297	0.291	1.3	1.45	0.148	
Small	0.160	0.159	0.3	0.28	0.778	
Medium	0.037	0.038	-0.8	-0.83	0.407	
Large	0.005	0.005	-0.6	-0.85	0.393	
Construction	0.223	0.225	-0.4	-0.48	0.633	
Wholesales	0.336	0.333	0.6	0.7	0.484	
Retail	0.193	0.196	-0.6	-0.71	0.479	
Region 2	0.017	0.015	0.9	0.99	0.324	
Region 3	0.011	0.010	0.8	0.77	0.439	
Region 4	0.048	0.048	0.2	0.23	0.815	
Region 5	0.013	0.013	-0.2	-0.25	0.802	
Region 6	0.005	0.005	-0.4	-0.48	0.634	
Region 7	0.040	0.040	-0.3	-0.39	0.694	
Region 8	0.107	0.108	-0.5	-0.57	0.571	
Region 9	0.042	0.040	1.0	1.17	0.242	
Region 10	0.073	0.072	0.3	0.25	0.801	
Region 11	0.012	0.013	-1.2	-1.24	0.213	
Region 12	0.213	0.217	-1.1	-1.2	0.232	
Region 13	0.138	0.137	0.5	0.58	0.564	
Region 14	0.021	0.020	0.7	0.76	0.45	
Region 15	0.095	0.094	0.7	0.71	0.475	
Region 16	0.035	0.035	0.1	0.07	0.946	
Region 17	0.000	0.000	0.5	0.75	0.453	
Region 18	0.001	0.001	0.0	-0.05	0.961	
Region 19	0.038	0.039	-0.6	-0.57	0.571	
Region 20	-	-	-	-	-	
EBIT margin (q2)	0.383	0.378	1.0	1.02	0.309	
EBIT margin (q3)	0.353	0.351	0.3	0.36	0.72	
EBIT margin (q4)	0.133	0.135	-0.6	-0.8	0.424	

Table A6: Balancing tests of observable characteristics between treated and control. Italy

Variable	Mean		t-test			Variance ratio
	Treated	Control	%bias	t	p>t	
Continuous variables						
Turnover (2015)	14.012	13.992	1.5	1.54	0.123	1.01
Turnover (2016)	14.093	14.077	1.2	1.28	0.199	1.02
Turnover (2017)	14.118	14.102	1.2	1.26	0.207	1.02
Turnover (2018)	14.139	14.123	1.3	1.32	0.187	1.02
Turnover (2019)	14.13	14.11	1.5	1.61	0.108	1.02
Fixed assets (log)	11.443	11.466	-0.9	-0.93	0.35	0.98
Current assets (log)	13.675	13.646	2.2	2.31	0.021	1.01
Material costs (log)	13.066	13.064	0.1	0.1	0.921	1.09*
Intangible fixed assets (log)	5.568	5.536	0.6	0.61	0.544	1.01
Categorical variables						
Loans (dummy)	0.445	0.445	-0.1	-0.08	0.938	
Capital (q2)	0.341	0.350	-2.0	-1.83	0.068	
Capital (q3)	0.187	0.180	1.8	1.71	0.088	
Capital (q4)	0.436	0.433	0.6	0.57	0.57	
Small	0.117	0.114	0.9	0.94	0.349	
Medium	0.023	0.022	0.5	0.6	0.552	
Large	0.004	0.004	0.5	0.65	0.517	
Construction	0.233	0.244	-2.7	-2.44	0.015	
Wholesales	0.280	0.276	0.9	0.85	0.394	
Retail	0.192	0.196	-1.1	-0.93	0.352	
Region 2	0.029	0.029	0.2	0.14	0.885	
Region 3	0.290	0.296	-1.5	-1.39	0.165	
Region 4	0.007	0.006	1.6	1.4	0.162	
Region 5	0.000	0.000	0.3	0.59	0.556	
Region 6	0.046	0.038	4.6	3.73	0.000	
Region 7	0.022	0.020	1.6	1.31	0.191	
Region 8	0.001	0.001	0.3	0.28	0.783	
Region 9	0.007	0.006	1.4	1.28	0.201	
Region 10	0.019	0.019	0.2	0.17	0.862	
Region 11	0.004	0.003	1.3	1.2	0.229	
Region 12	0.004	0.005	-0.6	-0.72	0.473	
Region 13	0.007	0.007	0.2	0.18	0.857	
Region 14	0.102	0.103	-0.2	-0.17	0.862	
Region 15	0.009	0.009	0.4	0.34	0.734	
Region 16	0.109	0.111	-0.8	-0.74	0.46	
Region 17	0.118	0.119	-0.1	-0.04	0.965	
Region 18	0.015	0.018	-2.4	-2.03	0.043	
Region 19	0.029	0.028	0.7	0.65	0.518	
Region 20	0.116	0.118	-0.5	-0.52	0.605	
EBIT margin (q2)	0.369	0.384	-3.1	-2.75	0.006	
EBIT margin (q3)	0.304	0.298	1.3	1.18	0.236	
EBIT margin (q4)	0.150	0.137	3.2	3.36	0.001	

Table A7: Number of observations excluded for being off-support

Model specification without pre-treatment outcomes				
<i>Country</i>	<i>Spain</i>		<i>Italy</i>	
Reason for exclusion	Firms	Obs.	Firms	Obs.
non-overlapping covariates	24	192	50	400
non-overlapping balancing score	15	120	273	2184
Total observation used	56,509	452,072	26,347	210,776

Model specification including pre-treatment outcomes				
<i>Country</i>	<i>Spain</i>		<i>Italy</i>	
Reason for exclusion	Firms	Obs.	Firms	Obs.
non-overlapping covariates	24	192	50	400
non-overlapping balancing score	33	264	266	2128
Total observation used	56,491	451,928	26,354	210,832

A.4 Robustness to alternative estimators and specifications

Tables A8 and A8 present the results obtained using alternative difference-in-differences (DiD) estimators. For each method, estimates are reported for models both with and without corrections for potential violations of the parallel trends assumption. The corrections (Columns 2 and 4) involve including pre-treatment outcomes in the set of matching covariates. It is important to note that when lagged outcomes are incorporated into the set of covariates, Z_i , the parallel trends assumption transforms into a conditional mean independence assumption. This implies that treatment is considered effectively random, conditional on the lagged outcome and other elements of Z_i . All models include the same set of observable characteristics. To test for violations of the parallel trends assumption, we follow the standard approach outlined by (Autor, 2003), by testing whether the lead terms in the event-study model are statistically indistinguishable from zero. Violations of the parallel trends assumption are ruled out if the interaction terms are jointly insignificant. The outcome of such tests are reported in the last row of each panel. Note that "PT outcomes" refers to pre-treatment outcomes while "PT test" refers to parallel trend test.

Table A8: Results of the different model specifications. Spain

Column	(1)	(2)	(3)	(4)
Turnover (log)	Matching DiD	Matching DiD + PT-outcomes	CS-DiD	CS-DiD + PT-outcomes
Treatment x 2020	-0.038*** (0.004)	-0.047*** (0.004)	-0.066*** (0.003)	-0.063*** (0.003)
Treatment x 2021	0.006 (0.004)	-0.004 (0.004)	-0.014*** (0.004)	-0.012*** (0.004)
Treatment x 2022	0.022*** (0.005)	0.012** (0.005)	0.003 (0.004)	0.005 (0.004)
Observations	452,024	451,936	452,192	452,192
Passes the PT test	No	Yes	No	Yes
Log (Employees)				
Treatment x 2020	0.008** (0.004)	-0.002 (0.004)	-0.019*** (0.003)	-0.009*** (0.003)
Treatment x 2021	0.017*** (0.004)	0.010** (0.004)	-0.009*** (0.004)	0.002 (0.003)
Treatment x 2022	0.026*** (0.005)	0.021*** (0.005)	0.003 (0.004)	0.016*** (0.004)
Observations	452,024	451,976	452,192	452,192
Passes the PT test	No	Yes	No	Yes
Total Assets (log)				
Treatment x 2020	0.083*** (0.003)	0.071*** (0.003)	0.067*** (0.002)	0.068*** (0.002)
Treatment x 2021	0.082*** (0.004)	0.069*** (0.004)	0.065*** (0.003)	0.064*** (0.003)
Treatment x 2022	0.068*** (0.004)	0.054*** (0.004)	0.051*** (0.003)	0.050*** (0.003)
Observations	452,024	451,888	452,192	452,192
Passes the PT test	No	Yes	No	Yes
EBIT margin (log)				
Treatment x 2020	-0.382*** (0.019)	-0.370*** (0.019)	-0.390*** (0.018)	-0.397*** (0.018)
Treatment x 2021	-0.097*** (0.018)	-0.081*** (0.017)	-0.067*** (0.017)	-0.074*** (0.016)
Treatment x 2022	-0.077*** (0.018)	-0.065*** (0.018)	-0.046*** (0.017)	-0.052*** (0.017)
Observations	452,024	452,080	452,192	452,192
Passes the PT test	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses. *** p< 0.01, ** p< 0.05, * p< 0.1. PT outcomes = Pre-Treatment outcomes; PT test = Parallel Trend Test.

Table A9: Results of the different model specifications. Italy

Column	(1)	(2)	(3)	(4)
Turnover (log)	Matching DiD	Matching DiD + PT-outcomes	CS-DiD	CS-DiD + PT-outcomes
Treatment x 2020	-0.047*** (0.006)	-0.040*** (0.006)	-0.065*** (0.005)	-0.058*** (0.005)
Treatment x 2021	0.001 (0.008)	0.011 (0.008)	0.004 (0.006)	0.013** (0.006)
Treatment x 2022	0.026*** (0.010)	0.035*** (0.010)	0.035*** (0.008)	0.041*** (0.008)
Observations	211,864	211,776	214,544	214,544
Passes the PT test	No	Yes	No	Yes
Log (Employees)				
Treatment x 2020	0.008* (0.005)	0.011** (0.005)	0.044*** (0.004)	0.045*** (0.004)
Treatment x 2021	0.018*** (0.007)	0.021*** (0.007)	0.056*** (0.005)	0.057*** (0.006)
Treatment x 2022	0.028*** (0.009)	0.032*** (0.009)	0.063*** (0.007)	0.062*** (0.007)
Observations	211,864	212,224	214,544	214,544
Passes the PT test	Yes	Yes	Yes	Yes
Total Assets (log)				
Treatment x 2020	0.048*** (0.004)	0.050*** (0.004)	0.044*** (0.004)	0.045*** (0.004)
Treatment x 2021	0.055*** (0.006)	0.056*** (0.007)	0.056*** (0.005)	0.057*** (0.006)
Treatment x 2022	0.058*** (0.008)	0.057*** (0.008)	0.063*** (0.007)	0.062*** (0.007)
Observations	211,864	212,160	214,544	214,544
Passes the PT test	No	Yes	No	Yes
EBIT margin (log)				
Treatment x 2020	-0.430*** (0.037)	-0.322*** (0.039)	-0.490*** (0.031)	-0.421*** (0.032)
Treatment x 2021	-0.150*** (0.033)	-0.039 (0.034)	-0.098*** (0.027)	-0.028 (0.027)
Treatment x 2022	-0.009 (0.035)	0.081** (0.037)	0.048 (0.032)	0.120*** (0.033)
Observations	211,864	212,016	214,544	214,544
Passes the PT test	No	Yes	No	Yes

Notes: Robust standard errors in parentheses. *** p< 0.01, ** p< 0.05, * p< 0.1. PT outcomes = Pre-Treatment outcomes; PT test = Parallel Trend Test.