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Covid-19 in Central America: Firm resilience and policy responses on employment

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Abstract

This paper examines how government support interacts with firm-level resilience capabilities in the reduction of layoffs among formal firms in Central America. Our analysis suggests that government support measures play a role in reducing the probability of layoffs among firms with *only* dynamic resilience capabilities (i.e., those that are developed *after* the pandemic onset). The effect of government support is not statistically different from the effect of static resilience capabilities alone (i.e., those that were present before the pandemic); thus, in firms with such capabilities, the effect of government support will be marginal. These results hold across sectors - exhibiting a marginally higher treatment effect in service sectors. Our results do not imply that Covid-19 supportive measures are to be disregarded, but instead raise the question of how government support policies could improve the allocation of support among firms in

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times of crises. Moreover, it underlines the necessity of policies that enhance resilience more broadly – a task that hints at structural issues and requires continuous government support in lieu of ad-hoc measures. © 2022 The Authors. Published by Elsevier Inc. on behalf of The Society for Policy Modeling. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

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1. Introduction

The decrease in firm sales and revenue as the result of the first impacts of the COVID-19 pandemic during 2020 led to a significant loss of employment throughout Central America. As a response to the crisis generated by the pandemic in 2020 and 2021, local governments increased public spending and implemented a wide range of policy measures to support local businesses: from credit, training, and fiscal relief, to facilitating digitization measures (World Bank, 2022). However, government assistance had very limited coverage. According to data from the World Bank's World Enterprise Survey, on average, only 10.7 % of firms in Central America received government support, with important variation across countries: this share was 21.3 % in Guatemala, 11 % in Honduras, 9.9 % in El Salvador, and 1.3 % in Nicaragua (World Bank, n.d.). Yet, it is in small firms, where the bulk of the labour force is concentrated, that the negative effects of the pandemic were felt the hardest (ILO, 2021; World Bank, 2022). This then raises the question on the actual protective impacts on employment of such support allocation.

This question becomes crucial in the context of resource-constrained local governments. Central American economies have limited ability to provide both monetary support and construct safety nets, bounded by the low level of public spending and revenues. For instance, government revenues in Central America represent less than 18 % of GDP, compared with 28 % of GDP in the seven largest Latin American economies (World Bank, 2012). Moreover, while Covid-19 fiscal stimulus in high-income countries constituted 10 % of GDP or more, with about 40 % dedicated to business support, developing countries allocated only between 1 % and 3 % of GDP, with about one-quarter designated to supporting firms (Cirera et al., 2021). This resource constraint therefore pushes local governments to allocate their support more efficiently to reach firms that are both hard-hit and economically viable, i.e., resilient (World Bank, 2012). More specifically, in the COVID-19 pandemic many firms in this region preferred lay-offs, and not suspensions, to avoid accumulating liabilities, and therefore government support policies also sought to reduce such practices. While preliminary reports show it did (MINECO, 2020), it is unclear by how much; moreover, little is known about how efficiently support was allocated: i.e., if support was given to firms that otherwise would have been forced to reduce their workforce, or to firms that, regardless of receiving it, would have not laid off employees.

Our paper contributes to the discussions on the role that government policy plays in mitigating the economic adverse effects of the Covid-19 - usually felt more strongly among the most disadvantaged (e.g., Arbolino & Di Caro, 2021; Kaicker et al., 2022). Namely, we investigate how firm-level resilience capabilities interact with government support in the reduction of lay-offs among formal firms in El Salvador, Guatemala, Honduras, and Nicaragua. We focus on how this support interacts with different forms of firm resilience, i.e., static and dynamic (Dormady et al., 2019; Rose, 2004, 2007), to assess how these measures impact the

probability of lay-offs. Such distinction of resilience capabilities allows for a more critical analysis of the effects of Covid-19 on formal firms, as well as policy responses; failure to do so can bias the estimates of firm-level resilience capabilities, and more importantly, the estimation of the overall effectiveness of government support on labour outcomes.

Our empirical approach consists of creating different counterfactual groups using a Markov Chain Monte Carlo (MCMC) simulation to understand which firms cope better with and without government support. This is followed by a comparison of the empirical cumulative distribution function (ECDF) of these groups using first-order stochastic dominance to assess in which group government support lay-offs are less likely to occur. We find that among most groups support policies play only a marginal role whereas in the dynamic resilient group receiving government support does shrink the probability of lay-offs.

The structure of our paper is as follows: [Section 2](#) offers a brief literature review of firm resilience literature review. The methodology considerations are explained in [Section 3](#). [Section 4](#) discusses results for the group-specific ECDF and group comparisons. Final considerations are given in [Section 5](#).

2. Theoretical framework

The existing literature distinguishes between static and dynamic (economic) resilience. The former is generally defined as the capacity of a system to cushion against damage or loss ([Rose, 2004](#)). On the one hand, static resilience refers to the actions that firms can take with existing resources in the aftermath of a shock which facilitate the recovery of the production output. Therefore, static resilience points to the actions and resources that were accumulated prior to the shock; thus, while their effect contributes to the recovery of a firm, they do not emerge in response to it ([Dormady et al., 2019](#)). Moreover, static resilience means that a firm reduces potential damages or losses through the efficient use of its resources ([Pant et al., 2014](#)), but it does not imply a quick response to shock. Dynamic resilience, on the other hand, does add a temporal dimension to the recovery ([Pal et al., 2014](#)); namely, it refers to the speed and ability to recover from a crisis ([Rose, 2004, 2007](#)). Thus, broadly speaking, the dynamic dimension of resilience points to the specific actions that are carried out in response to a shock, for instance, by investing in damage repairs and/or reconstruction efforts ([Pant et al., 2014](#)). Certainly, the effects of both dimensions are not mutually exclusive ([Rose, 2004](#)); however, this does not imply that if a firm exhibits one, it possesses both dimensions.

More recently, literature has conceptualized resilience as a process which materializes as a series of organisational capabilities or actions taking place (or emerging) in different points in time with respect to a shock. [Conz and Magnani \(2020\)](#) postulate there are different pathways, i.e., adaptive and absorptive, and each of these indicate different phases: they indicate $t-1$ as the proactive phase preceding the exogenous shock, t as the adaptive or absorptive phase occurring during the shock, and finally $t+1$ as the reactive phase when the shock has ended. The two dynamic cycles of adaptability and absorption only differ with regards to the firm's idiosyncratic response to the shock; adaptability implies resourcefulness and flexibility to adapt to the changes brought by the shock, while absorption implies robustness and agility to withstand the shock but not necessarily change because of it ([Conz & Magnani, 2020](#)). Similarly, [Duchek \(2020\)](#) argues that resilience is a meta-capability characterised by the ability to respond to adverse events before, during and after they occur. The stages of the resilient process possess a set of organisational capabilities and drivers that are either already present or developing. Furthermore, [Dormady et al. \(2019\)](#) distinguish resilience based on the actions undertaken by

the firm: for instance, inherent resilience is reflected in actions such as relocation (i.e., moving activities and data to a different location) while adaptive resilience considers technological change (i.e., improvising the production process without requiring a major investment expenditure) and management effectiveness (e.g., flexible procedures and working hours, minimised reporting requirements). Finally, in the context of the Covid-19 pandemic, Bai et al. (2021) explore the ability of companies to adapt jobs and tasks to remote working as a proxy for a company's digital resilience and its effects on firm performance. Due to the increase of work-from-home (WFH) adoption during the Covid-19 pandemic, the study explicitly measures both pre- and post-outbreak WFH levels. Their contribution highlights the role of WFH as a valid indicator for resilience capabilities, an important finding that justifies this paper's choice of indicators.

Innovation is one of the key capabilities that contribute to a firm's resilience as it allows firms to adapt and respond to changes in the environment (Kamalahmadi & Parast, 2016; Santos-Vijande & Alvarez-González, 2007). Several studies have confirmed the positive relationship between firm resilience and innovation investments (Reinmoeller & Van Baardwijk, 2005), the degree of innovation (Golgeci & Ponomarov, 2015), and product innovativeness (Akgun & Keskin, 2014). Moreover, Sabahi and Parast (2020) establish that a firm's innovation resources influence the development of resilience capabilities via knowledge sharing, agility, and flexibility. They conclude that a firm with a more innovative environment will exhibit higher resilience. This empirical link justifies thus innovation activities and investments as proxy for resilience capabilities.

A key postulation that is explored in this paper is the interaction between government support and resilience capabilities. Dormady et al. (2019), for instance, tie resilience capacities to the existence of government policy levers. Subsequently, a firm's economic adaptive resilience is affected by government post-disaster assistance programs. Certainly, government policy supports can both aid in the establishment of static resilience capabilities pre-disaster, and the mitigation of negative effects through dynamic economic resilience during and post-disaster. In this study, we focus on understanding the latter and its interaction with the already existing (innovative) characteristic to better understand how policy support is best allocated. Empirical evidence on the issue is largely restricted to developed countries or focuses on larger firms. For instance, a study in the Netherlands during the Covid-19 pandemic finds that state support was most efficiently allocated to firms that experienced both lower turnover expectations but also exhibited better management practices (Groenewegen et al., 2021). Evidence suggests this policy strategy in particular helped SMEs to maintain their levels of employment and production.

An additional point of discussion is in which form governmental support schemes for firms prove most effective and should therefore be delivered. Although recent research has argued traditional financial support measures that seek to boost aggregate demand and provide liquidity, fail to recover the capacity to restore employment when activity is depressed due to health concerns (Chetty et al., 2020). For instance, Cirera et al. (2021) show that in the case of middle-income and high-income countries, wage subsidies and direct cash transfers, as well as access to credit proved to be the most effective means of helping firms address such liquidity shortages and reduce worker layoffs. In contrast, tax support and payment deferrals proved to be the least effective policies in addressing these issues. Similarly, in the case of Central American economies, Bruhn (2020) showed that in Mexico, firms that received wage subsidies conditional on maintaining workers in the aftermath of the global financial crisis outperformed those that did not receive such assistance. Importantly, such assistance should ideally provide short-term

breathing rooms for firms and enhance their long-term resilience capabilities, as discussed above. Notably, governmental assistance in the form of monetary transfers and access to credit has been shown to correlate with both a higher probability of investing in digital solutions and subsequently higher future expected sales growth.

Based on the above, we define a framework of resilience in which static capabilities is a general category of resources and abilities a firm accumulated prior to the shock, i.e., the pandemic onset in 2019, whereas dynamic capabilities refer to the specific responses after it. While static resilience has been previously characterised by resource efficiency (Pant et al., 2014; Rose, 2004), our definition relies on redundancy, i.e., the ability of a firm to accumulate of resources and know-how, which contribute to the firm’s robustness when shocked. Similarly, the definition of dynamic capabilities hinges upon the adaptive actions that allow a firm to minimise losses. Certainly, the latter may be linked to the former, but as explained in Rose (2004) a firm’s adaptive behaviour is determined by its ingenuity to act differently than in “business as usual” manner. Furthermore, the uncertainty and length that characterised the Covid-19 crisis, stresses the critical role of flexibility - i.e., the capacity for rapid decision-making and ability to internally re-adapt processes and strategies to changing conditions (Conz & Magnani, 2020). Following a temporal distinction, we consider innovation inputs, i.e., R&D and technology investments, and outputs, i.e., product and/or service innovations, carried out before and after the onset of the pandemic - as proxies for static and dynamic resilience capabilities, respectively.¹ Finally, the choice of lay-offs to measure resilience follows the definition of resilience - the ability of an individual or entity to deflect damage and/or losses in the face of an adverse event (Rose, 2004, 2007). It is a logical assumption, then, that if a firm can operate despite the demand and/or supply shock brought about by the Covid-19 crisis due to higher resilience, the probability that it will reduce its workforce would be lower.

3. Method

3.1. Model

We begin by estimating a latent variable which captures static resilience effects, η^0 , before the Covid-19 pandemic, using a basic linear probability model:

$$\eta^0 = \Gamma\xi + \epsilon^{\eta_0} \tag{1}$$

where Γ is a matrix of covariates capturing the static resilience firm characteristics and ϵ^{η_0} is the error. The former includes the following variables: whether the firm introduced an innovation to the market three years prior to the baseline year and whether the firm invested in R&D at the time the baseline survey was conducted.² In the same manner, we then define a second latent variable which captures dynamic resilience effects, η^1 , after the onset of the Covid-19 pandemic:

$$\eta^1 = \Lambda\kappa + \epsilon^{\eta_1} \tag{2}$$

¹ For static innovation, we include innovation inputs (R&D investments prior to the pandemic) and innovation outputs (introduction of new services or products to the market prior to the pandemic). For dynamic resilience we consider innovation inputs (investments in new technologies) and innovation outputs during Covid-19, i.e., new service or product introduced to the market, as well as organizational innovations expressed as a remote work arrangement.

² The baseline year for all countries is 2016 - except for Guatemala, where it is 2017.

where Λ is a matrix of covariates capturing the dynamic resilience firm characteristics and ε^{η^1} is the error. The former includes the following variables: whether the firm introduced a new product or service during Covid-19, whether it invested in a digital solution, software or new equipment during Covid-19, and the share of workers that work from home; in this regard, this refers to the remote work arrangement (if any) as a response Covid-19.

Further, we define our main equation whereby we estimate the probability of a lay-off at the firm-level:

$$y = X\beta + \tau + \eta_0 + \eta_1 + \varepsilon^y \tag{3}$$

where X is a matrix of firm-level controls (i.e., log of sales in December 2019, log of firm size, firm age, a dummy for country effects, a dummy to capture whether the firm is located in the capital city, the number of weeks the establishment had to close due to the Covid-19 contingency, type of ownership, and industry³), and τ is the treatment, i.e. whether the firm in question received government support.

We employ a Bayesian framework in which the model estimations rely on the specification of a likelihood function and the distribution of priors of the parameters. Given Eqs. (1)–(3) the quasi-likelihood function of the model takes the following form:

$$L(\eta_0, \eta_1, x, y|\phi) = \prod_{i=1}^N N(\eta_i^0 | \Gamma\xi) N(\eta_i^1 | \Lambda\kappa) N(y_i | X\beta + \tau + \eta_0 + \eta_1) \tag{4}$$

The vector of the parameters in the model $\varphi = (\xi, \kappa, \beta, \tau)$ is estimated with flat uninformative priors, which is the default. Furthermore, we define the prior distribution of the two latent variables (η^*), as a multivariate normally distributed $N(\eta^*, \Omega_{\eta^*})$ with a Ω_{η^*} fixed variance. We assume that the information of these latent variables η^0 and η^1 , is contained within the data generation process of Eq. (3), but also the linear equations with the factors correlated to static resilience (1) and dynamic resilience (2).

For the estimation, Eq. (4) is transformed following Bayes’s rule to calculate the joint posterior distribution of the parameters. Following the definition by Palomo et al. (2007), we represent the Bayes Equation with the likelihood function given the priors φ , and the marginal likelihood function in the denominator of the following expression:

$$\pi(\eta^0, \eta^1, \phi|x, y) = \frac{\mathcal{L}(\eta^0, \eta^1, x, y|\phi) \times \pi(\phi)}{\int L(\eta^0, \eta^1, x, y|\phi) d\eta^0 d\eta^1 d\phi} \tag{5}$$

The close form solution of the Eq. (5) is analytically challenging to solve. Therefore, the parameters are estimated generating draws from the joint posterior distribution using a Markov Chain Monte Carlo (MCMC) algorithm as in Stan (2021). The algorithm was run for $s = 3000$ iterations with four chains. The convergence of the parameters was assessed graphically and also using the $R - hat \approx 1$ when the model is at equilibrium (Gabry & Goodrich, n.d.).

³ The industries include the following: ‘food’, ‘garment & textiles’, ‘furniture’, ‘other manufacturing’, ‘retail’, and ‘other services’.

Table 1
Counterfactual groups.

R (S)	R (D)	T	Groups
x	x	x	$R(D + S) + T$
x	x		$R(D + S)$
x		x	$R(S + T)$
	x	x	$R(D + T)$

3.2. MCMC simulation

After the estimation of parameters of Eq. (3), including the latent variables, we perform a counterfactual analysis of four different scenarios (see Table 1) to assess the effect of firm-level resilience (i.e., static, and dynamic) and government support (i.e., the treatment). The probability estimations which allow for the comparison across scenarios are calculated using an inverse Logit function. To simplify the interpretation of the results, we re-write the effect of resilience.

capabilities as $\eta^0 = S$ and $\eta^1 = D$ and government support as $\tau = T$. The effect of total resilience is expressed as $R(D + S)$ and the independent static and dynamic resilience as $R(D)$ and $R(S)$, respectively. Table 1 defines the four counterfactual scenarios.

To compare the performance of the counterfactual groups, we further assess their empirical cumulative distribution function (ECDF) using first-order stochastic dominance (Levy, 1992). For this purpose, we use draws from the model using MCMC to calculate the distribution of the proportion of times in which one group exhibits a higher lay-off probability than a counterfactual group.

3.3. Data and variables

To build our database we use data from the World Bank Enterprise Survey for El Salvador, Guatemala, Honduras, and Nicaragua; this includes data from the standard surveys carried out between 2016 and 2017, and the COVID-19 follow-ups conducted in 2020 (World Bank, n.d.). The latter specifically deal with changes in sales, business practices and government support during the COVID-19 pandemic. The dataset originally contained 1762 observations; due to item nonresponse, our final sample was reduced to 510 observations.

The dependent variable is a binary variable, *reduced workforce*, that captures whether the firm had any lay-offs due to the pandemic; this variable takes the value of one if respondents reported having laid off at least one employee, and zero, otherwise.⁴ As seen in Table 2 about one fourth of the firms sampled laid off employees due to the outbreak.

The treatment variable, *support*, is also built based on the answers of the Covid-19 follow-ups. It takes the value of one if the firm had received any form of national or local government support at the time of the survey, and zero, otherwise. About 12 % of firms in our sample reported having had some government support, as seen in Table 2. Yet the share varies widely across the Central American countries in the sample, as earlier shown (see Table 1).

⁴ Namely, the question was: "How many workers have been laid off due to the COVID-19 outbreak?"

Table 2
Summary statistics.

Variables	Mean	SD	Min	Max
Reduced workforce	0.26	0.44	0.00	1.00
Log of sales 2019	15.03	2.76	7.60	24.76
Log of size	3.36	1.40	1.10	7.90
Age	30.90	17.93	6.00	131.00
Capital city	0.56	0.50	0.00	1.00
Weeks closed	1.75	4.81	0.00	22.00
Support	0.12	0.32	0.00	1.00
Innovation	0.34	0.47	0.00	1.00
R & D	0.15	0.36	0.00	1.00
Innovation Covid-19	0.29	0.45	0.00	1.00
Remote work (%)	7.16	17.90	0.00	100.00
Investment Digital	0.31	0.46	0.00	1.00

Regarding variables linked to static resilience, [Table 2](#) shows that about 34 % of firms had engaged in product and/or service innovation, and 15 % had invested in R&D prior to the survey baseline year. For dynamic variables, about 29 % of the firms introduced innovations to the market since the Covid-19 outbreak, and about the same (31%) invested in some form of digital technology. The average firm had about 7 % of its working force working from home in response to the contingency.⁵ This share, while low, is consistent with the potential share of remote working in other developing countries (5.5–23 %), as identified in [Saltiel \(2020\)](#).

The summary statistics are presented in [Table 2](#). Concerning control variables, it is worth noting that the *weeks closed* variable shows that whereas some firms had to close up to 22 weeks, the average firm did so for less than two weeks. The sample includes firms which operate formally across six sectors, with most firms belonging to the food sector followed by textiles and furniture manufacturing, as seen in [Table 3](#).

4. Results

We first explore the results of the analysis of the empirical cumulative distribution functions (ECDF) of each scenario defined in [Table 1](#).

[Fig. 1](#) shows that there is no difference in the predicted probability (overlapping curves) between the group that benefits from both forms of resilience capabilities and government support, $R(D + S) + T$, and, the group with static and dynamic resilience capabilities but no treatment, $R(D + S)$. Additionally, the group with static resilience capabilities and government support $R(S) + T$ exhibits the same function as the latter groups.

The group with *only* dynamic capabilities and treatment $R(D) + T$ shows a small but noticeable reduction in the predicted probability of a lay-off, as seen [Fig. 1](#).

⁵ Concerning how closely variables move with each other, pairwise correlation coefficients, shown in [Table 4](#) (in Appendix), indicate that previous innovation efforts are not necessarily strongly correlated to innovativeness after the onset of Covid-19.

Table 3

Sectors.	
Sector name	Obs
Food	143
Textiles & Garments	122
Furniture	127
Other Manufacturing	39
Retail	28
Other Services	51

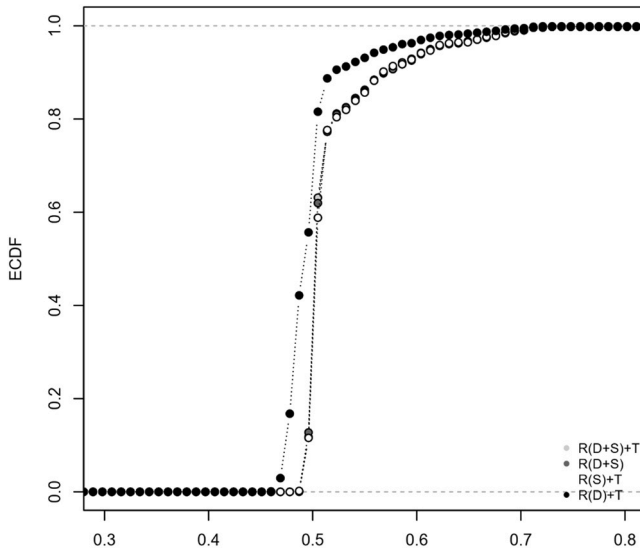


Fig. 1. ECDF of counterfactual groups.

Predicted Probability of Lay-off in Fig. 1. To illustrate this change, the predicted probability of a lay-off being equal to or less than 0.5 in the $R(D) + T$ group is around 0.6, whereas in the other groups it stands at around 0.4.

The results therefore suggest that firms with more dynamism, and less robustness (in this case, linked to the accumulation of innovation capacities prior to the crisis), would react more to government support with respect to employment. This hints, then, at some kind of trade-off between robustness and adaptive traits - possibly as a result of resource redundancy. The results from the analysis of the empirical cumulative distribution function (ECDF) confirm that there are differences - albeit marginal - in the predicted probability of a lay-off among the

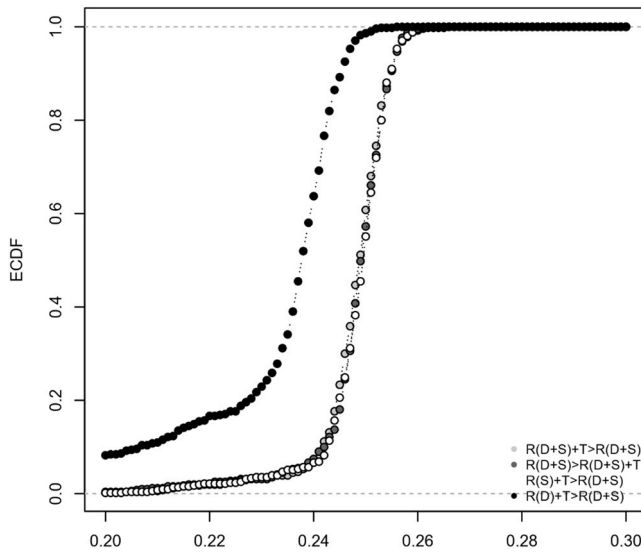


Fig. 2. ECDF of counterfactual groups.

counterfactual groups. To interpret the results, we use the concept of first-order stochastic dominance to compare the difference between pairs of ECDF.

In Fig. 2, we can observe four comparisons between the four groups ($R(D + S) + T > R(D + S)$; $R(D + S) > R(D + S) + T$; $R(S) + T > R(D + S)$; and $R(D) + T > R(D + S)$). We report the ECDF of the proportion of times in which one group showed higher lay-off probabilities than the other. The curve on top, $R(D) + T > R(D + S)$, shows that the probability of lay-offs in the group with dynamic resilience plus government support, $R(D+S)+T$, is lower than the group with effects of both forms of resilience but without government support, $R(D + S)$, in line with the ECDF of the $R(D) + T$ group in Fig. 1.

The following curve $R(D + S) + T > R(D + S)$ shows the proportion of the times in which the probability of a lay-off with both forms of capabilities and treatment, $R(D + S) + T$, was higher than the group without treatment, $R(D + S)$. The opposite proposition is tested in the curve, $R(D + S) > R(D + S) + T$: it depicts the proportion of times in which the probability of a layoff in the group with both forms of resilience and no support, $R(D + S)$, was larger than the group with both forms of resilience and government support, $R(D+S)+T$. The last curve, $R(S)+T > R(D +S)$, represents the proportion of times in which the probability of a lay-off in firms with static capabilities with treatment, $R(S) + T$, was higher than the firms that had both forms of resilience but no treatment $R(D + S)$. The overlap of these three curves shows that the effect of government support was not significantly higher than the effect of static resilience alone - also reflecting the ECDFs of these groups in Fig. 1.

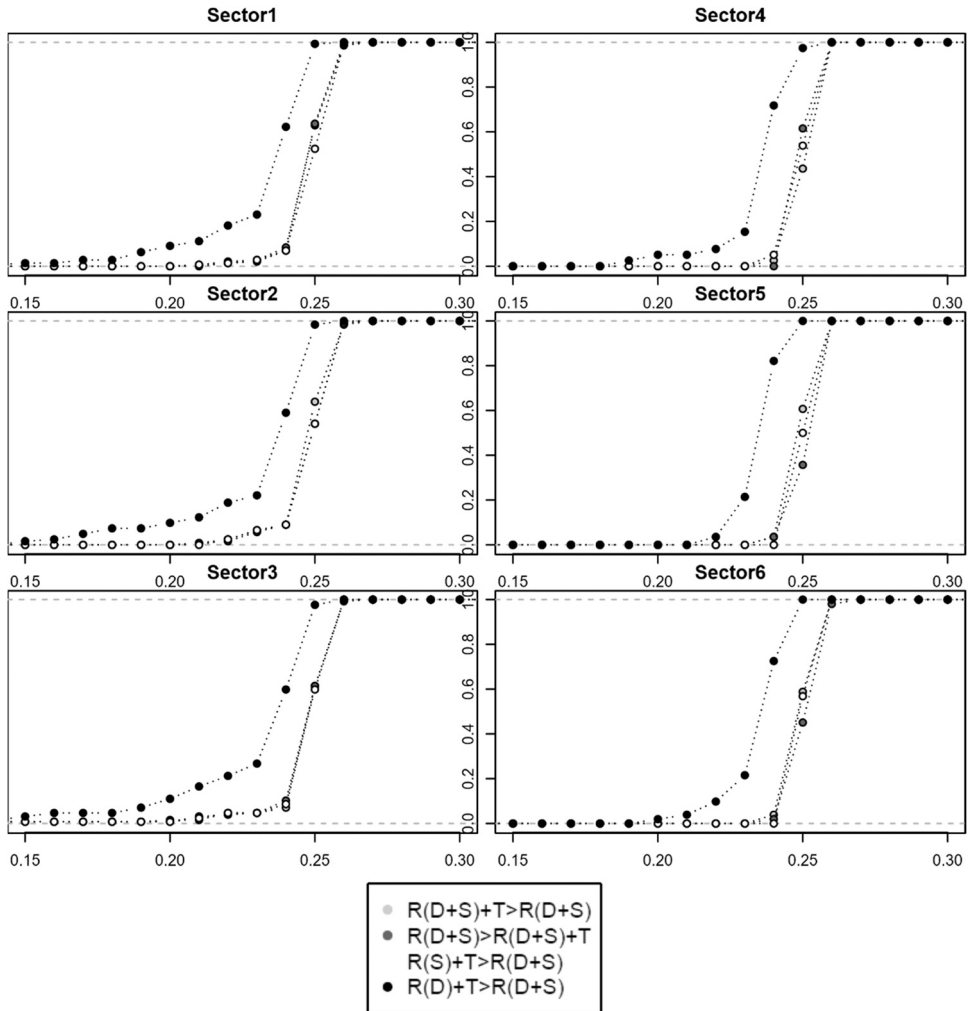


Fig. 3. Comparison ECDF of counterfactual groups by sector.

Our analysis is extended by further decomposing effects, i.e., the probability of a lay-off due to Covid-19, across the six sectors available in our data (Food; Textiles & Garments; Furniture; Other manufactures; Retail; and Other Services). Fig. 3 compares the difference between pairs of ECDF of the counterfactual groups (in Fig. 2) by sector; it shows that there is consistency with previous results and that there is, generally speaking, little variation across sectors.

However, we can observe that the treatment effect seems to be marginally stronger in Retail (Sector 5 in Fig. 3) and in Other Services (Sector 6): the curve, $R(D) + T > R(D + S)$, shows more noticeably that the probability of lay-offs in the group with dynamic effects plus government support, $R(D + S) + T$, is lower than the group with only resilience, $R(D + S)$. This slightly larger treatment effect found in services is possibly attributed to a somewhat stronger interaction between public support and dynamic capabilities - which are naturally easier to implement in retail and services.

5. Conclusion

The results of our study indicate that despite coverage limitations, government support measures in four countries of Central America (El Salvador, Guatemala, Honduras and Nicaragua) have had a positive impact on employment by reducing the probability of lay-offs among the formal firms that receive it. Nonetheless, this effect is not equally observed among firms. Namely, we find that the effect of government support is not statistically different from the effect of static resilience *alone* with respect to lay-off probabilities. In other words, government support in firms with a history of innovative capabilities (e.g., measured by R&D investments) will not increase or decrease its probability of lay-off. In these firms, their robustness - which in turn is linked to their historical innovation capacity/investments – is what determines how many of their employees they are able to keep on their payroll, rather than one-off measure. This finding supports previous studies (e.g. [Akgun & Keskin, 2014](#); [Golgeci & Ponomarov, 2015](#)).

Contrariwise, we find that government support does reduce the probability of lay-offs in firms that exhibit dynamic capabilities *alone*. This means that policy support in firms that are able to change their business-as-usual operations – but are not long-standing resourceful innovators – does make a difference with respect to how many employees they can keep in the payroll. It is reasonable to assume that, in these firms, resources are limited but managerial practices - proxied by the capacity to react amidst the pandemic shock – allows them to make the most of government support. This supports previous empirical findings in developed countries ([Groenewegen et al., 2021](#)). Furthermore, the results from our simulation hold across sectors - exhibiting a marginally higher treatment effect in service sectors.

These considerations raise a number of questions with respect to government support allocation and how to best guide it. Is government support going to more firms with static resilience where it is less likely to have an effect in protecting employment? or to more dynamic (yet less resource-abundant) firms, where it is more likely to have an effect? In Latin America, firms with R&D capabilities, i.e., exhibiting static resilience capabilities, are predominantly large companies. Moreover, 99.5 % of the industrial sector is comprised by SMEs which generate 60 % of formal employment ([OECD, 2021](#)). Thus, it is reasonable to assume that the majority of people in this sector are employed in firms that fit the ‘dynamic-capabilities-only’ profile: firms that mobilised resources to work from home and/or invested in some form of digital technology during the pandemic but do not have enough resources to have an R&D department.

Previous studies on SMEs in the United States of America have found that applying to government support has had a positive impact on resilience, though allocation decisions ought to incorporate firm size, number of employees, firm ownership gender, as well as spread awareness of the availability of aid programs ([Katare et al., 2021](#)). Further evidence by [Cirera et al. \(2021\)](#) showed that smaller firms are about half as likely to access support as large firms and that in comparison firms in high-income countries are five times more likely to receive public support than firms in low-income countries.

Consequently, we found that Central American government support has been allocated to larger firms, which are more likely to exhibit static resilience capabilities and where such effect

is less likely to make a difference in terms of employment outcomes. This allocation decision is to be expected, as [Katare et al. \(2021\)](#) also highlight that financial institutions generally prioritize large loans over small ones, arguing that understanding how to implement support programs and aid at the local level must be a critical aspect in policy design.

We then argue that a more strategic allocation of policy measures, i.e., one that looks at the existing capacities and resources of the firm, is justified – especially in settings with limited public resources, such as in Central America. Such a strategy raises, however, the issue of how to design guidelines and options to efficiently make such distinctions. Within this context, our findings pose further questions and add to previous discussions relating to the shape of effective government support schemes for smaller firms such as direct cash transfers or access to credit to improve long-term resilience capabilities in conjunction with short-term disaster relief.

Likewise, our findings stress the importance of developing resilience-related capabilities, especially those that emerge in response to the Covid-19 crisis - such as digitisation investments and remote work among less resourceful firms, typically micro and small firms. These may be harder to develop in a developing country as they require other complementary public infrastructure investments (e.g., Internet and logistics), but may have a broader impact for employment retention.

Our results do not imply at all that Covid-19 supportive measures are to be disregarded. Instead, these raise the question of how government support policies could improve the allocation of support among firms in times of crises, and, in particular, of how policymakers can achieve aid to be directed to those firms with the highest possible impact. Moreover, it underlines the necessity of policies that enhance resilience more broadly - a task that speaks of more structural issues and that surely requires stronger and continuous government support in lieu of ad-hoc measures.

Ultimately, our findings call for additional research that takes into account informal firms as well as measuring the size of government support given. Corresponding results would perhaps find a steeper reduction in lay-off probabilities. Furthermore, country-specific effects or disparities in availability and awareness of government policies should also be further investigated. Finally, our model could also be replicated to study the impact of government support in reducing lay-offs across other economies and find whether their results are comparable.

Appendix

See appendix [Table 4](#).

Table 4
Correlation of variables.

	Reduced work.	Log of sales	Log of size	Age	Capital city	Weeks closed	Support	Innovation	R&D	Innov. Covid-19	Remote work (%)	Invest. Digital
Reduced work.	1											
Log of sales	0.169***	1										
Log of size	0.090*	0.584***	1									
Age	0.004	0.082	0.132**	1								
Capital city	0.118**	0.233***	0.242***	0.150***	1							
Weeks closed	0.081	-0.027	0.01	-0.038	-0.028	1						
Support	0.022	-0.058	0.094*	0.046	0.019	0.229***	1					
Innovation	-0.028	0.196***	0.208***	0.045	0.132**	-0.048	-0.04	1				
R&D	0.091*	0.256***	0.302***	0.110*	0.145**	-0.04	0.033	0.223***	1			
Innov. Covid-19	0.072	0.150***	0.148***	0.001	0.097*	0.655***	0.211***	-0.03	0.01	1		
Remote work (%)	0.093*	0.177***	0.124**	0.075	0.147***	0.043	0.095*	0.130**	0.021	0.047*	1	
Invest. Digital	0.087*	0.108*	0.148***	0.011	0.027	-0.063	0.088*	0.150***	0.136**	-0.047	0.157***	1

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