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COVID-19 in Central America: effects of firm resilience and policy responses on employment

Beatriz Calzada Olvera,[1,2] Mario Gonzalez-Sauri,[1,3] Federico Louvin,[4] and David-Alexander Harings Moya[4]

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Abstract: With data from the World Bank Enterprise Survey, this paper examines how firm-level resilience capabilities interact with government support in the reduction of lay-offs among formal firms in Central America. We estimate two latent variables to approximate resilience-related capabilities before (static) and after (dynamic) the COVID-19 pandemic. We create four counterfactual groups using a Markov chain Monte Carlo simulation to assess which resilience capabilities help firms cope better, with and without government support. We find that support policies play a marginal role among most groups, except in the dynamic resilient group, where receiving government support does shrink the probability of lay-offs.

Key words: capabilities, resilience, COVID-19, Central America, government support

JEL classification: C63, D01, L25, O30

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[1] United Nations University–Maastricht Economic and Social Research Institute on Innovation and Technology, Maastricht, Netherlands; [2] Erasmus University Rotterdam, Netherlands; [3] Utrecht University, Netherlands; [4] Maastricht University, Netherlands; corresponding author: calzadaolvera@ihs.nl

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Information and requests: publications@wider.unu.edu

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Katajanokanlaituri 6 B, 00160 Helsinki, Finland

1 Introduction

Combined with Mexico, Central America, as of April 2021, reported a total of 3.3 million cases of COVID-19 and 230,000 deaths (ECDC 2021). Having reached the region at the end of March 2020, the virus remains prevalent in most countries except Nicaragua, with reported infections in Honduras and Guatemala reaching 375,000 and 600,000, respectively, by late October 2021. As the pandemic persists, the possibility of renewed national lockdowns, reduced exports, and the hampering of tourism recovery all loom large over the region's weakened economies, which were projected to see an average decline of GDP of at least 3 per cent in 2020 (IMF 2020).

In addition to the public health impact, the scale of the economic fallout from the pandemic has only begun to emerge. A recent survey of the private sector across the region found that sales had fallen by an average of 50 per cent. In addition, more than half of the surveyed companies said they had reduced their total number of permanent employees (World Bank 2021). Indeed, a study of the effects of the first lockdown in Mexico revealed a decrease of 5.4 per cent in formal employment, with small and medium-sized enterprises (SMEs) struggling to recover as quickly as their larger counterparts (Balmori de la Miyar et al. 2021). Given the importance of these firms to their economies, local governments should provide them with support to cope with the pandemic, but it might prove to be a hard task, given the low level of public spending and revenues (World Bank 2012). This resource constraint should push local governments to allocate their limited support more efficiently.

Though existing studies have explored effects of firm-level resilience capabilities before, during, and after a crisis, as seen in Conz and Magnani (2020), none have integrated the effect of resilience capabilities with that of governmental support on employment. The theory generally suggests that there are two main forms of resilience (Dormady et al. 2019; Rose 2004, 2007). We build on these broad definitions to conceptualize firm resilience capabilities as follows: the survival of firms is determined by the capabilities developed as a reaction to the crisis, coined as *dynamic resilience*. At the same time, firms possess existing capabilities developed prior to the shock, known as *static resilience*. This distinction allows for a more critical analysis of the effects of COVID-19 on formal firms.

In this paper, 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. Namely, we focus on how this support interacts with firm resilience to provide a better assessment of how these measures impact the probability of lay-offs. Failing to disentangle the effect of government support during crises can bias the estimates of firm-level resilience capabilities, as well as the effectiveness of those measures. Our sample ($n \approx 500$) is extracted from the World Bank Enterprise Survey (standard and COVID-19 follow-ups).

We first estimate two latent variables to approximate static resilience and dynamic resilience capabilities using relevant covariates. To assess whether static resilience capabilities help firms cope better than those with dynamic resilience, with and without government support, we create four counterfactual groups using a Markov chain Monte Carlo (MCMC) simulation.

Finally, we compare the empirical cumulative distribution function (ECDF) of these groups using first-order stochastic dominance (Levy 1992) 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 review of the firm resilience literature, which provides the foundations for building a resilience capabilities framework at the firm level; we also discuss an overview of government measures to support firms in the region of study. The methodology considerations—that is, probability estimations and MCMC simulation—are explained in Section 3.

Section 4 discusses the results for the group-specific ECDF and group comparisons. Final considerations are given in Section 5.

2 Theoretical framework

2.1 Theory and empirical background

The literature on resilience covers a large number of fields, methodologies, and levels of analysis. Resilience itself is a versatile concept. It is commonly understood as a trait of individuals who manage to successfully cope with difficulties and uncertainties (Conz and Magnani 2020). Nevertheless, firm-level research has placed its focus on system resilience (Norris et al. 2008), supply chains (Ambulkar et al. 2015; Parast et al. 2019; Sabahi and Parast 2020), and shocks internal to the firm (Brewton et al. 2010; Duchek et al. 2020). Firm resilience after external shocks, though present in recent works from Pal et al. (2014) and Penades et al. (2017), has been understudied. Most importantly, the role of government support and its interaction with resilience capabilities has, to our knowledge, not been researched yet.

Economic resilience exists at different levels (e.g., the firm, household, market, or macroeconomic level) and is typically categorized as either static or dynamic, as explained in Rose (2004, 2007). The former dimension is generally defined as the capacity of a system to cushion against damage or loss (Rose 2004). Following authors have built on this definition to characterize its attributes. Pant et al. (2014), for instance, highlight that this dimension possesses a 'time-independent impact' on an entity. Dormady et al. (2019) then add that, at the firm level, 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; yet, while their effect contributes to the recovery of a firm, they do not emerge in response to it. Moreover, whereas static resilience means that a firm reduces potential damages or losses through the efficient use of its resources (Pant et al. 2014), it does not imply a quick response to shock nor a speedy recovery.

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 possess both dimensions.

Recent theoretical studies have taken a deeper look into the concept of resilience as a process (hence its temporal dimension) that materializes as a series of organizational capabilities. Conz and Magnani (2020) review the existing body of research on the resilience of firms in the business and management field. After reporting more than 60 different definitions of resilience, they establish a conceptual framework based on an adaptive and an absorptive pathway. More specifically, for each pathway, 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. For each phase, specific capabilities are owned, deployed, or developed in response to the shock. 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 in order to adapt to the changes brought by the shock, while absorption implies robustness and agility in order to withstand the shock, but not necessarily change because of it (Conz and Magnani 2020).

Similarly, Duchek (2020) identifies the three successive resilience stages of anticipation, coping, and adaptation. According to this framework, resilience is a meta-capability characterized by the ability to respond to adverse events before, during, and after they occur. The stages of the resilient process possess a set of organizational capabilities and drivers that are either already present or developing. Overall, this temporal distinction for resilient capabilities is a key building block for this paper's framework. A comparison between the frameworks of Rose (2004), Conz and Magnani (2020), and Duchek (2020) is presented in Table 1.

Table 1: Firm-level resilience capabilities: theory

<table>
<tr><th>Authors</th><th>Concept</th><th>Temporal dimension</th></tr>
<tr><td>Rose (2004)</td><td>Resilience refers to the response to disasters that enables an entity to avoid some potential losses. The response can be inherent (i.e. ability under normal circumstances) or adaptive (i.e. ability in crisis situations due to ingenuity or extra effort). Economic resilience is highly behavioural; it requires ingenuity and resourcefulness applied during and after an event.</td><td>Inherent capabilities: [$t-1$]; adaptive capabilities [t],[$t+1$]</td></tr>
<tr><td>Conz and Magnani (2020)</td><td>Resilience is identified through capabilities deployed at different stages: before an adverse event (proactive); during (absorptive and adaptive); and after the event (reactive). Specific capabilities are then deployed through two pathways at each stage:
The absorptive path consists of redundancy, the ability to reserve resources, [$t-1$]; robustness, the ability to resist shocks; redundancy, the ability to accumulate resources, [$t-1$]; robustness, the ability to resist shocks,[t]; and agility, the ability to provide a quick organizational response when dealing with turbulence, [$t+1$].
The adaptive path refers to resourcefulness, the ability to accumulate different diversified assets and resources, [$t-1$]; adaptability, the dynamic adaptation through actions such as adjusting, recombining of resources, self-renovating, and continuous reconstruction, [t]; and flexibility, the capability of implementing rapid decision-making processes, quick internal communication, and fast learning to quickly adapt routines and strategies to changing conditions,[t+ 1].</td><td>Proactive capabilities [$t-1$]; absorptive and adaptive capabilities [t]; reactive capabilities [$t+1$].</td></tr>
<tr><td>Duchek (2020)</td><td>Resilience is defined as the ability to effectively respond to adverse events, before, during, and after them. Accordingly, there are three successive stages of the resilience process: anticipation, coping, and adaptation. Resilient organizations not only respond to the past (reactive action) or to current issues (concurrent action), but also to future ones (anticipatory action). These stages of the resilience process underlie a set of organizational capabilities and drivers (knowledge base, resource availability, social resources, power, and responsibility).</td><td>Anticipation capabilities [$t-1$]; coping capabilities [t]; adaptation capabilities [$t+1$]).</td></tr>
</table>

Source: authors' elaboration.

Recent studies have begun to empirically measure the different capabilities in firms described previously—though *how* to do this varies extensively as there is little consensus on what resilience actually constitutes (Duchek 2020). Moreover, the many dimensions associated to the temporal aspect adds another layer to the analysis that may or may not be included. Pal et al. (2014), for instance, study the concept of resourcefulness and other traits linked to the capabilities discussed in Conz and Magnani (2020). The indicators are collected via survey and measured on the basis of the firm's self-assessment.

The operationalization of capabilities in Dormady et al. (2019) distinguishes, as seen in Table 2, between inherent and adaptive resilience capabilities. The estimation of adaptive resilience necessarily includes inherent resilience, while inherent resilience is estimated as a standalone set of actions observed in firms. Among the indicators employed for inherent resilience they include relocation (i.e. moving activities and data to a different location). For adaptive resilience, they take into consideration the inherent resilience indicators but add technological change (improvising the production process without requiring a major investment expenditure) and management effectiveness (e.g. flexible procedures and working hours, minimized reporting requirements).

Table 2 shows other contributions to empirical studies on firm-level resilience. Of special relevance in the context of the COVID-19 pandemic is the study by Bai et al. (2021). Their research centres around the concept of 'digital resilience', which they measure as a firm's WFH (work from home) feasibility in response to its labour demand. More concretely, they use the ability of companies to adapt jobs and tasks to so-called remote working as a proxy for a company's resilience ability and its effects on firm performance and investments. Due to the increase of WFH adoption as a result of the COVID-19 pandemic, the study explicitly measures both pre- and post-outbreak levels using a firm-level index. Its findings subsequently support the theoretical classification of static and dynamic resilience. Additionally, 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 as well.

Table 2: Firm-level resilience capabilities: empirical work

Authors	Concept	Indicators
Pal et al. (2014)	Resilient firms require a combination of: resourcefulness (material, financial, social, network, and intangible resources), dynamic competitiveness (flexibility, redundancy, robustness, and networking), and learning and culture (leadership, collectiveness, and employee wellbeing)	Firm's own assessment of resourcefulness, competitiveness, and culture through a survey using Likert-scale questions.
Dormady et al. (2019)	Builds on Rose's (2004) framework to measure *inherent resilience* and *adaptive resilience*, which is exemplified by changing technology, devising new market mechanisms, or new government post-disaster assistance programmes.	Both inherent and adaptive resilience include supply chain-related abilities, and relocation (e.g. moving business activities and/or data to a new location). Additionally, adaptive resilience includes management efficiency and technological change.
Bai et al. (2021)	Digital resilience is measured by the firm's WFH feasibility to their labour demand. The ability/feasibility for companies to adapt jobs and tasks to remote working serves as a proxy for a company's resilience. Due to the increase of WFH adoption as a result of the COVID-19 pandemic, the paper explicitly measures both pre- and post-outbreak levels using a firm-level index.	Firm-level WFH feasibility index (percentage of workforce that has the WFH option) using US job postings from Burning Glass Technologies with a WFH feasibility indicator. This shows each firm's position on the WFH feasibility index (low or high), used to assess resilience next to sales, net income, capital and software expenditures, stock returns, and total assets.

Source: authors' elaboration.

Kamalahmadi and Parast (2016) establish that innovation is one of the key capabilities that contribute to a firm's resilience—although its role has been somewhat overlooked in the contemporary literature. Innovation is crucial to a firm's growth and long-term survival, and it is essential for adaptation and responding to changes in the environment (Santos-Vijande and Álvarez-González 2007). Empirically, a few studies have established a link between innovation and resilience. The study of Reinmoeller and Van Baardwijk (2005) concludes that only when enough resources are allocated to innovation are firms able to overcome disturbances and disruptions and adapt to rapid changes. Likewise, Gölgeci and Ponomarov

(2015) establish a positive relationship between the firm's innovativeness and degree of innovation with (supply chain) resilience. In line with these studies, Akgün and Keskin (2014) study the relationship between resilience capacity, product innovation, and firm performance, and find a significant relationship between variables linked to resilience capacity and a firm's product innovativeness. Based on the above, 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 thus justifies innovation activities and investments as proxies for resilience capabilities.

2.2 Government support and firms

An additional postulation that is explored in this paper is the interaction between government support and resilience characteristics. 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 programmes. Therefore, we see resilience as a process in which government support can both aid in the establishment of static resilience capabilities pre-disaster, and in the mitigation of negative effects through dynamic economic resilience during and post-disaster.

However, it can be argued that, in the absence of government support pre-disaster, the impact of post-disaster policies and support can depend on a firm's own level of static resilience capacity. This is an especially pressing issue in the context of the examined Central American economies, as their ability to provide both monetary support and construct safety nets is limited by the low level of public spending and revenues. For instance, government revenues in Central America represent less than 18 per cent of GDP, compared with 28 per cent of GDP in the seven largest Latin American economies (World Bank 2012). This resource constraint pushes local governments to allocate their limited support more efficiently to reach firms that are both hard-hit and economically viable—that is, resilient (World Bank 2012). A study by Groenewegen et al. (2021) showed that in the case of the Netherlands, COVID-19 state support was most efficiently allocated to firms that experienced both lower turnover expectations but also exhibited better management practices. In their case, COVID-19 state aid came in the form of direct loan subsidies and financial support for different business segments, as well as tax deferrals and the suspension of bankruptcy regulation (Groenewegen et al. 2021). Evidence suggests that such forms of government support in particular have helped SMEs to maintain their levels of employment and production.

In the case of the four examined Central American countries, the extent of government support varied considerably. As identified by CEPAL (2020), the number of business support measures announced by the national governments ranged from 17 in Honduras, to 10 in Guatemala, 8 in El Salvador, and only 2 in Nicaragua by July 2020. Moreover, with the exception of Nicaragua, all other governments had made direct financial aid or credit policies available for companies.

Preliminary data show that such government policies can greatly aid in the reduction of lay-offs. For instance, according to the Ministry of Economy of Guatemala (*Ministerio de Economia of Guatemala*) there were around 174,087 workers from 16,629 enterprises currently receiving aid from the Employment Protection Fund by the end of 2020 (MINECO 2020). Moreover, anecdotal evidence discussed in their report on economic recovery shows that many enterprises otherwise preferred to lay-off, and not suspend, their employees to avoid accumulating labour liabilities and other benefits. In contrast, Nicaraguan companies largely received monetary support from external organizations, such as the *Banco Centroamericano de Integracion Economica* (BCIE), which resulted in the maintenance of around 6,000 employees (BCIE 2021). These observations are in support of the data from the World Bank Enterprise Survey. As shown in Table 3, Guatemala had the highest percentage of companies receiving support (21 per cent), while Nicaragua had the lowest (1.3 per cent).

Table 3: Government support by country

Support	El Salvador	Honduras	Guatemala	Nicaragua	Total
No	428	176	185	226	1,015
	90.11%	88.89%	78.72%	98.69%	89.27%
Yes	47	22	50	3	122
	9.89%	11.11%	21.28%	1.31%	10.73%
Total	475	198	235	229	1,137
	100.00	100.00	100.00	100.00	100.00

Source: authors' elaboration based on World Bank's Enterprise Survey data.

2.3 Dynamic and static resilience capabilities

For the purpose of our study, we define a framework of resilience in which static capabilities is a general category of resources and abilities a firm has accumulated prior to the shock (i.e. before the pandemic onset in 2019), whereas dynamic capabilities refer to the specific responses after it. While static resilience has been previously characterized by resource efficiency (Pant et al. 2014; Rose 2004), our definition rather relies on redundancy—that is, the ability of a firm to accumulate resources and know-how which contribute to the firm's robustness when shocked, following the conceptualization of Conz and Magnani (2020). Similarly, the definition of dynamic capabilities hinges upon the adaptive actions that allow a firm to minimize 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 ability to act differently than it would in a 'business as usual' manner. Furthermore, the uncertainty and length that characterized the COVID-19 crisis stresses the critical role of flexibility—that is, the capacity for rapid decision making and the ability to internally re-adapt processes and strategies to changing conditions (Conz and 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 is able to 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 that captures static resilience effects, η^0, before the COVID-19 pandemic, using a basic linear probability model:

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

where $\mathbf{\Gamma}$ 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

[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—that is, new services or products introduced to the market, as well as organizational innovations expressed as a remote working arrangement.

survey was conducted.[2] In the same manner, we then define a second latent variable that captures dynamic resilience effects, η^1, after the onset of the COVID-19 pandemic:

$$\eta^1 = \mathbf{\Lambda}\varkappa + \varepsilon^{\eta_1} \tag{2}$$

where $\mathbf{\Lambda}$ 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 the COVID-19 pandemic, whether it invested in a digital solution, software, or new equipment during the pandemic, and the share of workers that work from home; in this regard, this refers to the remote work arrangement (if any) as a response to COVID-19.

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

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

where $\boldsymbol{X}$ 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 industry[3]), and τ is the treatment—that is, 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 Equations 1–3 the quasi-likelihood function of the model takes the following form:

$$\mathscr{L}(\eta_0, \eta_1, \boldsymbol{x}, \boldsymbol{y} \mid \varphi) = \prod_{i=1}^{N} \mathscr{N}(\eta_i^0 \mid \mathbf{\Gamma}\xi)\mathscr{N}(\eta_i^1 \mid \mathbf{\Lambda}\varkappa)\mathscr{N}(\boldsymbol{y}_i \mid \boldsymbol{X}\beta + \tau + \eta_0 + \eta_1) \tag{4}$$

The vector of the parameters in the model $\varphi = (\xi, \varkappa, \beta, \tau)$ 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 $\mathscr{N}(\eta^*, \mathbf{\Omega}_{\eta^*})$ with a $\mathbf{\Omega}_{\eta^*}$ fixed variance. We assume that the information of these latent variables, η^0 and η^1, is contained within the data generation process of Equation (3), but also the linear equations with the factors correlated to static resilience (Equation 1) and dynamic resilience (Equation 2).

For the estimation, Equation 4 is transformed following Bayes' 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:

$$\pi(\eta^0, \eta^1, \varphi \mid \boldsymbol{x}, \boldsymbol{y}) = \frac{\mathscr{L}(\eta^0, \eta^1, \boldsymbol{x}, \boldsymbol{y} \mid \varphi) \times \pi(\varphi)}{\int \mathscr{L}(\eta^0, \eta^1, \boldsymbol{x}, \boldsymbol{y} \mid \varphi) \mathrm{d}\eta^0 \mathrm{d}\eta^1 \mathrm{d}\varphi} \tag{5}$$

The close form solution of Equation 5 is analytically challenging to solve. Therefore, the parameters are estimated generating draws from the joint posterior distribution using an MCMC algorithm as in Stan (2021). The algorithm was run for s= 3,000 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 and Goodrich 2021).

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

[3] The industries include 'food', 'garment and textiles', 'furniture', 'other manufacturing', 'retail', and 'other services'.

3.2 MCMC simulation

After the estimation of parameters of Equation 3, including the latent variables, we perform a counterfactual analysis of four different scenarios (Table 4) to assess the effect of firm-level resilience (i.e. static and dynamic) and government support (i.e. the treatment). The probability estimations that allow for the comparison across scenarios are calculated using a logit approach.

We compare the ECDF of these groups using first-order stochastic dominance (Levy 1992) to assess in which group government support lay-offs are less likely to occur.

Table 4: 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)*

Source: authors' elaboration.

3.3 Data and variables

To build our database we use data from the World Bank Enterprise Surveys 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. The data set originally contained 1,762 observations; due to item non-response, 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 1 if respondents reported having laid off at least one employee, and 0 otherwise.[4] As seen in Table 5, about one-quarter of the firms sampled laid off employees due to the outbreak.

Table 5: 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

Source: authors' elaboration.

The treatment variable, *support*, is also built based on the answers to the COVID-19 follow-ups. It takes the value of 1 if the firm had received any form of national or local government support at the time of the survey, and 0 otherwise. About 12 per cent of firms in our sample reported having had some government support, as seen in Table 5. Yet the share varies widely across the Central American countries in the sample, as shown in Table 3.

Regarding variables linked to static resilience, Table 5 shows that about 34 per cent of firms had engaged in product and/or service innovation, and 15 per cent had invested in R&D prior to the survey baseline

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

year. For dynamic variables, about 29 per cent of the firms introduced innovations to the market since the COVID-19 outbreak, and about the same (31 per cent) invested in some form of digital technology. The average firm had about 7 per cent of its workforce working from home in response to the pandemic.[5] This share, while low, is consistent with the potential share of remote working in other developing countries (5.5–23 per cent), as identified in Saltiel (2020).

The summary statistics are presented in Table 5. 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 that operate formally across six sectors, with most firms belonging to the food sector followed by textiles and furniture manufacturing, as seen in Table 6.

Table 6: Sectors

Sector name	Obs.
Food	143
Textiles and garments	122
Furniture	127
Other manufacturing	39
Retail	28
Other services	51

Source: authors' elaboration.

4 Results

We first explore the results of the analysis of the ECDF of each scenario defined in Table 4.[6] To simplify the interpretation of the results, we rewrite 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.

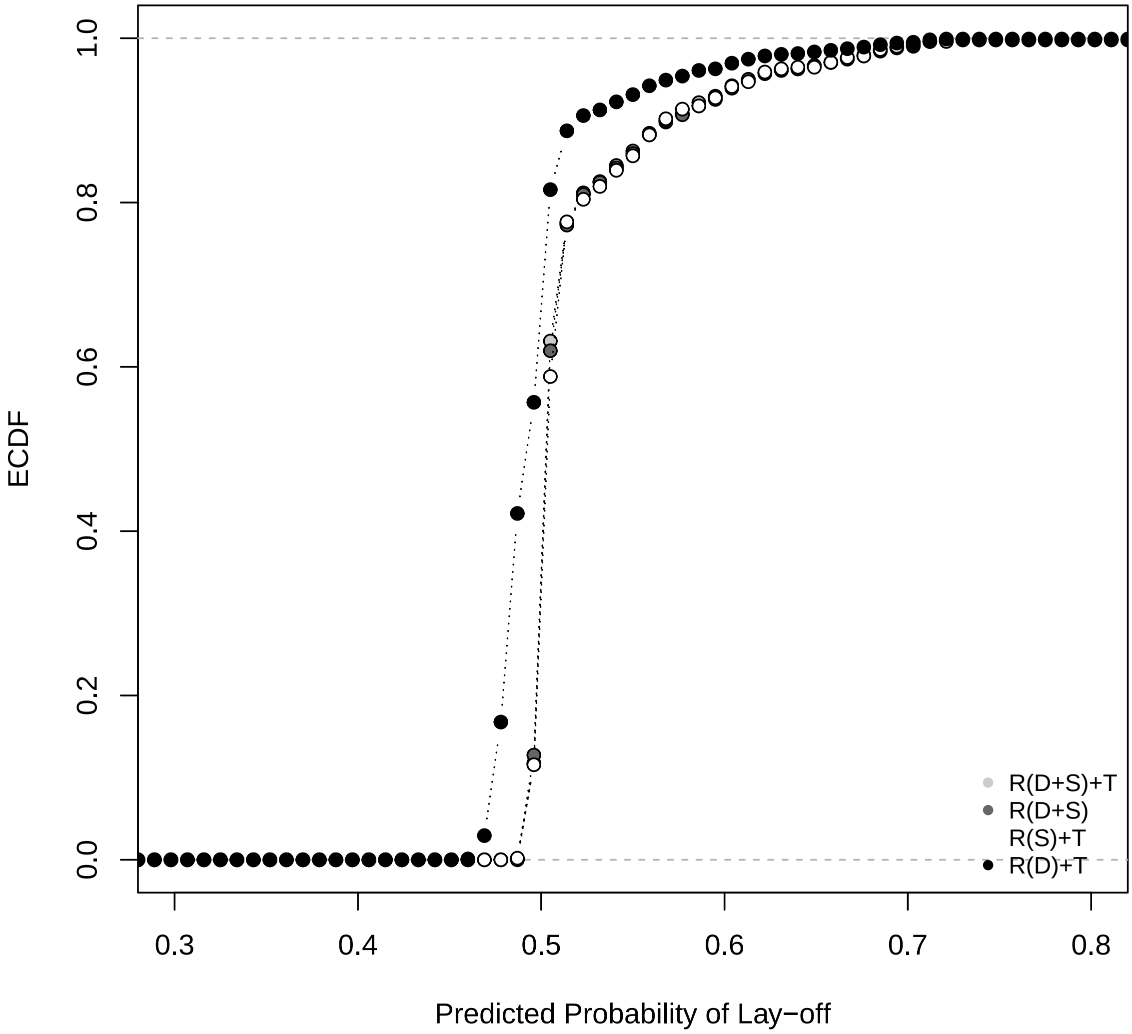
Figure 1 shows that there is no difference in the predicted probability (overlapping curves) between the group that benefits from both forms of resilience capabilities and government support, $R(D+S)+T$, and the group with static and dynamic resilience capabilities but no treatment, $R(D+S)$. Additionally, the group with static resilience capabilities and government support, $R(S)+T$, exhibits the same function as the latter groups. These results suggest that the probability of laying off workers is primarily driven by the resilience endowments that firms accumulate before a crisis, rather than the treatment. In other words, firms with static resilience, while robust, seem to be less sensitive to support measures with respect to lay-off decisions.

Furthermore, the results indicate that 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 in Figure 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.

[5] Concerning how closely variables move with each other, pairwise correlation coefficients, shown in Table A1 in Appendix A, indicate that previous innovation efforts are not necessarily strongly correlated to innovativeness after the onset of COVID-19.

[6] The estimation results of the latent variables in Equations 1 and 2 are presented in Tables A2 and A3 in Appendix A. The resulting $R-hat$ values are close to 1, indicating that the model is at equilibrium, allowing for a reliable estimation in the counterfactual analysis. It is worth mentioning that coefficients of the latent variables presented in these tables are unitless, and therefore lack a direct, substantive interpretation.

Figure 1: ECDF of counterfactual groups



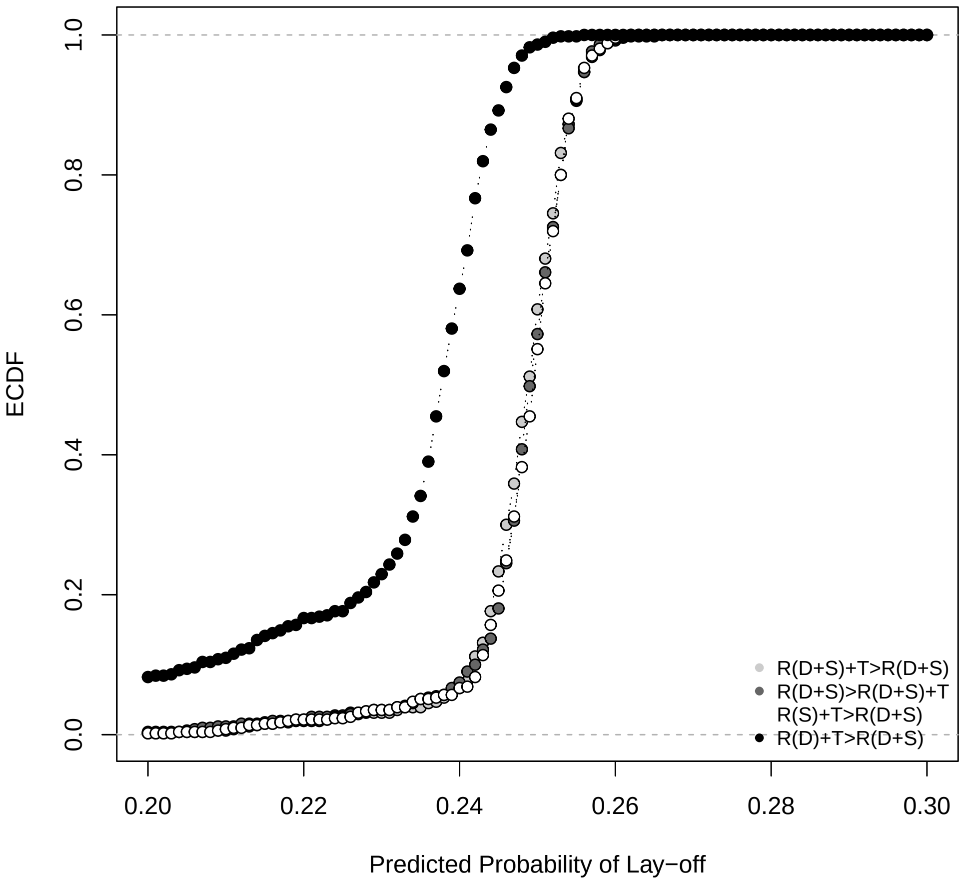
Source: authors' calculations.

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 adaptivity traits—possibly as a result of resource redundancy.

To explore further the difference in probability between groups, we calculate the distribution of the proportion of times in which one group exhibits a higher lay-off probability than a counterfactual group. The results from the analysis of the ECDF confirm that there are differences—albeit marginal—in the predicted probability of a lay-off among the counterfactual groups. To interpret the results, we use the concept of first-order stochastic dominance to compare the difference between pairs of ECDF $F(y_a) > F(y_b)$.

In Figure 2 we can observe four comparisons ($R(D+S)+T > R(D+S)$; $R(D+S) > R(D+S)+T$; $R(S)+T > R(D+S)$; and $R(D)+T > R(D+S)$), with the vertical axis representing the proportion of times in which one group showed higher lay-off probabilities than the other. The horizontal axis represents the predicted probability of a lay-off.

Figure 2: Comparison ECDF of counterfactual groups



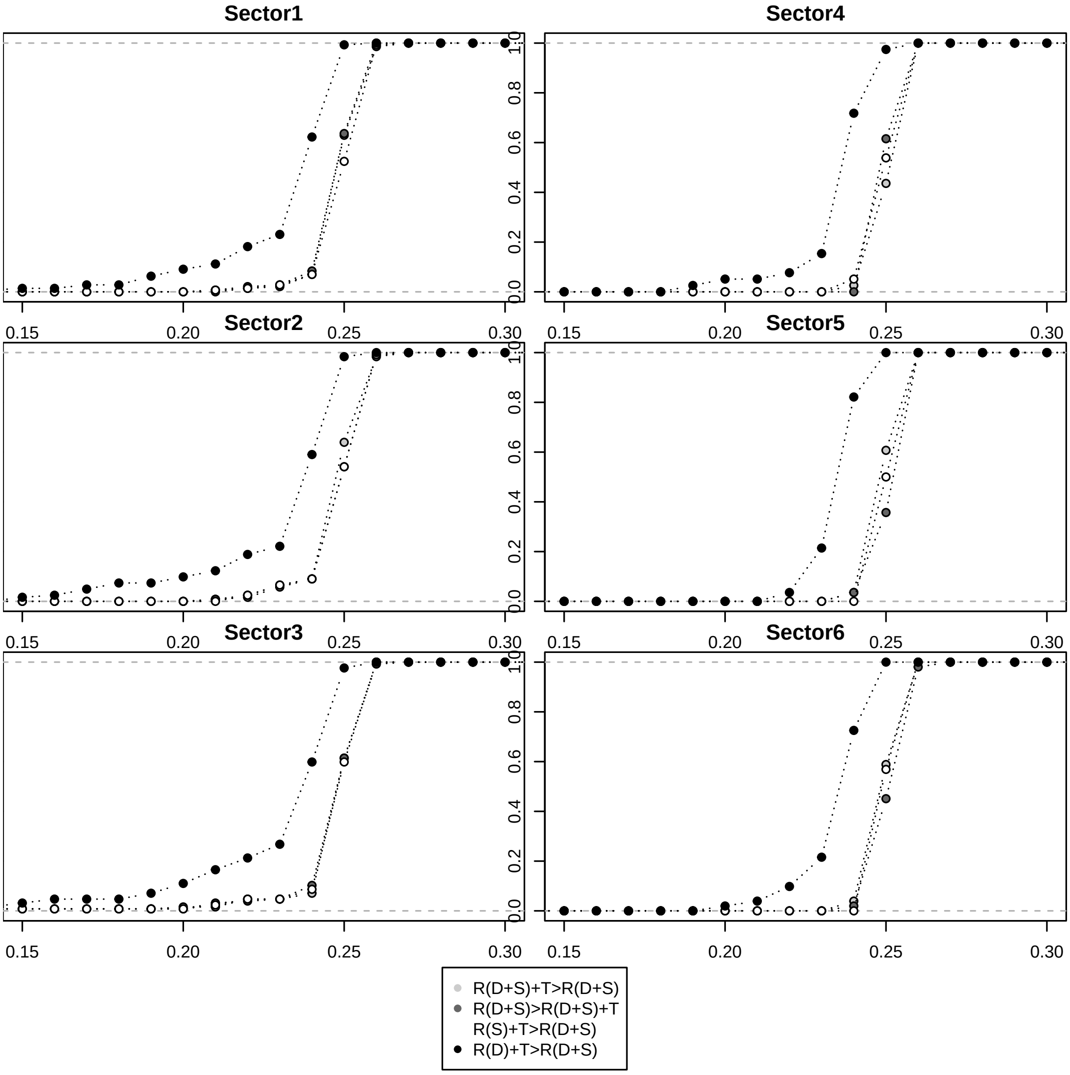
Source: authors' calculations.

The curve on top, $R(D)+T > R(D+S)$, shows 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 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 Figure 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 $R(D+S) > R(D+S)+T$, which depicts the proportion of times in which the probability of a lay-off 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 Figure 1.

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 and garments, furniture, other manufactures, retail, and other services). Figure 3 compares the differences between pairs of ECDFs of the counterfactual groups (in Figure 2) by sector; it shows that there is consistency with previous results and that there is, generally speaking, little variation across sectors.

Figure 3: Comparison ECDF of counterfactual groups by sector



Note: sectors: (1) food; (2) textiles and garments; (3) furniture; (4) other manufactures; (5) retail; (6) other services.
Source: authors' calculations.

However, we can observe that the treatment effect seems to be marginally stronger in retail (sector 5 in Figure 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.

4.1 Summary and discussion

In short, the results of our analysis suggest that government support measures do play a role in reducing the probability of lay-offs among firms with dynamic capabilities alone. Yet, we also find that the effect of government support does not seem to be statistically different from the effect of static resilience alone with respect to lay-off probabilities. Moreover, the results from our simulation hold across sectors—exhibiting a marginally higher treatment effect in service sectors.

Ultimately, the above raises the question of how public support is allocated—that is, is support going to more robust firms where it is less likely to have an effect in employment? Or to more dynamic (and yet less resource-abundant) firms, where it is more likely to have an effect? It is not unreasonable to assume that there are many more people employed in firms that fit the 'dynamic-capabilities-only' profile: firms that mobilized resources to work from home and/or invested in some form of digital investment during the pandemic but do not have enough resources to have an R&D department. Equally so, there are probably fewer people employed in firms that would fit the 'static capabilities profile': firms with a well-established innovation and R&D trajectory. Considering this, an adequate allocation of support would make a difference for employment outcomes—especially in settings with limited public resources, such as Central America.

Likewise, our findings stress the importance of developing resilience-related capabilities—especially those that emerge in response to the COVID-19 crisis—such as digitization investments. These may be harder to develop in a developing country as these require other complementary public infrastructure investments (e.g. internet and logistics), but may have a broader impact for employment.

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, namely by reducing the probability of a lay-off among the formal firms that receive it. However, the reduced probability of a lay-off is not observed equally among firms. Our results show that the 'protective' effects on employment derived from government support simply enhance the already-existing resilience at the firm level, especially if dynamic (i.e. observed after the onset of the COVID-19 pandemic).

These results, however, do not imply at all that COVID-19 supportive measures are to be disregarded. Instead, these results raise the question of how government support policies could improve the allocation of support among firms in times of crises. In particular, how policy-makers 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 of government policies should also be further investigated. Finally, our model could be replicated to study the impact of government support in reducing lay-offs across other economies and find whether their results are comparable.

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Appendix

Table A1: Correlation of variables

	1	2	3	4	5	6	7	8	9	10	11	12
Reduced workforce	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	0.010	–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	–0.040	1				
R&D	0.091*	0.256***	0.302***	0.110*	0.145**	–0.040	0.033	0.223***	1			
Innov. COVID-19	0.072	0.150***	0.148***	0.001	0.097*	0.655***	0.211***	–0.030	0.010	1		
Remote work (%)	0.093*	0.177***	0.124**	0.075	0.147***	0.043	0.095*	0.130**	0.021	0.047	1	
Investment digital	0.087*	0.108*	0.148***	0.011	0.027	–0.063	0.088*	0.150***	0.136**	–0.047	0.157***	1

Source: authors' elaboration.

Table A2: Covariates of static resilience

	Mean	0.50%	99.50%	R-hat
Innovation	0.083***	0.009	0.145	1.007
	(0.001)			
R&D	0.211***	0.11	0.311	1.007
	(0.001)			

Source: authors' elaboration.

Table A3: Covariates of dynamic resilience

	Mean	0.50%	99.50%	R-hat
Innovation COVID-19	–0.009	–0.053	0.03	1.086
	(0.003)			
Remote work(%)	0	–0.001	0	1.056
	(0)			
Investment digital	0.007	–0.017	0.035	1.033
	(0.001)			

Source: authors' elaboration.