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Medium-term urban business recovery after COVID-19: cross-country evidence after the outbreak

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Abstract.

To identify factors associated with medium-term business recovery, this study analyzes large-scale survey data on businesses located in diverse urban contexts around the world. While most studies of business recovery focus on the short term, the factors influencing short-term recovery may differ from those important in the medium term. This study provides cross-country evidence four to five years after the COVID-19 outbreak, based on a survey of 3,454 firms across seven global regions, including major cities in Canada, the United States, the European Union, New Zealand, South Africa, Thailand, and Japan, with 35% of firms located in downtown districts.

Across 26 variables, including policy measures, business characteristics, and strategies, several consistent patterns emerge. Non-governmental mentoring and training show the strongest positive association with sales recovery, exceeding the effects of loans and subsidies, highlighting the importance of non-financial support. By contrast, smaller firms (1–19 employees) exhibit persistently lower recovery levels and rely more heavily on personal funds, indicating structural vulnerability. While some conventional comparisons align with prior expectations, substantial heterogeneity is observed across regions and sectors. In particular, regional context and sectoral composition significantly influence the effectiveness of adaptation and policy measures. These findings provide new cross-country and urban-level evidence on medium-term SME recovery and highlight the importance of tailored, region- and sector-specific policy design to strengthen business resilience against future systemic shocks.

Keywords: COVID-19, Medium-term business recovery, SME resilience, Business adaptation, Governmental and non-governmental support, Cross-country analysis

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1 Introduction

The COVID-19 pandemic and associated lockdown measures generated unprecedented shocks to businesses worldwide, particularly in urban economies characterized by dense interactions and service-oriented activities. While aggregate indicators suggest that many economies have largely recovered, less attention has been paid to the medium-term recovery trajectories of small and medium-sized enterprises (SMEs). Persistent revenue gaps, debt accumulation, and uneven sectoral rebounds may indicate that recovery dynamics remain incomplete and heterogeneous across regions (Erdiaw-Kwasie et al., 2023).

Business-level characteristics are widely recognized in the literature as shaping vulnerability and recovery speed. Previous post-disaster studies document delayed recovery among sole proprietorships, women-owned firms, and small enterprises (Helgeson et al., 2022). Ownership structure, firm age, and location, including whether a firm is located in a central business district, may further shape resilience (Marshall et al., 2015; Josephson et al., 2017; Coad et al., 2023; Zutshi et al., 2021). For example, even within urban areas, businesses situated in downtown or in central business districts, compared with those in surrounding neighborhoods, may follow distinct recovery trajectories due to shifts in mobility patterns, consumption behavior, and work styles enabled by digital technologies (Brown and Cowling, 2021). Such location-specific effects are likely to vary across sectors.

However, recovery is not determined solely by inherent characteristics. During the pandemic, many firms implemented adaptation strategies, including digital transformation, operational restructuring, and business model innovation. Although numerous studies investigated the situation 1–2 years beyond the COVID-19 outbreak, there is limited understanding of whether these measures contributed to sustained recovery beyond short-term stabilization.

Policy responses likewise differed substantially across countries (IMF, 2021; Chang et al., under review). Beyond direct financial instruments such as subsidies and low-interest loans, many governments expanded non-financial support, including mentoring and business training. The relative effectiveness of these instruments, particularly over the medium term and across diverse institutional contexts, has not yet been systematically evaluated.

To address these gaps, this study analyzes survey data from 3,454 firms across seven regions: Canada (Vancouver and Calgary), the United States (Miami and Los Angeles), Europe represented by the Netherlands (Amsterdam) and the EU excluding the Netherlands, New Zealand (primarily from Auckland and Christchurch), South Africa (Cape Town), Thailand (Bangkok), and Japan (Osaka), from July 2024 to May 2025[1]. The diversity of policy environments and sectoral structures provides a useful empirical setting for evaluating heterogeneous recovery outcomes. Notably, 35.1% of respondents are located in downtown areas, offering insight into recovery dynamics in urban cores. Furthermore, 44.7% of the businesses are micro and small businesses (fewer than 20 full-time employees), underscoring the potential vulnerability of smaller businesses.

[1] This study was conducted as part of the New Frontiers in Research Fund (Government of Canada; special calls on pandemic recovery). The case study regions were selected to cover six patterns defined by the relationship between the stringency index and economic support index, as developed by the University of Oxford. Further details are provided in Chang et al. (under review).

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In total, we examine 26 factors encompassing business characteristics, policy interventions, and adaptation strategies, to assess their effects on sales recovery. Using an inverse probability of treatment weighting (IPTW) approach combined with outcome regression, we estimate doubly robust average treatment effects on the treated (ATT). This framework enables a systematic comparison of heterogeneous factors within a unified empirical setting.

Although observational data cannot eliminate all sources of bias, the large multi-region dataset provides robust evidence on the determinants of medium-term SME recovery and offers insights relevant to business sustainability conditions and more targeted policy design.

2 Literature review and datasets

2.1 Literature review

In the more than five years after the onset of the COVID-19 pandemic, a vast body of research has examined its impacts on businesses (e.g., Chang et al., 2022). The following review focuses on three aspects particularly relevant to this study: urban recovery, cross-country comparisons, and medium-term effects, with emphasis on business-level or small-spatial-scale analyses. Studies analyzing firm characteristics, business adaptation, and policy impacts in specific national or regional contexts are discussed alongside our empirical findings where relevant.

2.1.1 Urban recovery contexts

Several studies evaluate the impact of COVID-19 on urban businesses from the perspective of economic resilience. Sheng et al. (2024), using large-scale firm-level data for Beijing, show that infection risk and sectoral exposure, particularly in wholesale/retail and entertainment sectors, significantly increased firm exit rates. Similar findings emerge from European firm-level studies, which highlight the roles of firm capabilities, institutional connectedness, and policy support in shaping business outcomes (Chit et al., 2023).

Chetty et al. (2024), using large-scale consumer and small-business revenue data in the United States, demonstrate highly uneven economic impacts across income groups and locations. High-income households sharply reduced in-person spending in March 2020, severely cutting revenues of small businesses in affluent urban areas and triggering large, persistent job losses among low-wage workers. Although spending and job postings recovered by late 2021, low-wage employment remained depressed in hard-hit areas.

Endo and Kato (2025) provide additional insights into urban recovery using nighttime light data. They find that stay-at-home policies had stronger negative economic impacts in cities where individual-level financial support was more generous, possibly reflecting resource constraints on local recovery. They also report that cities with higher pre-pandemic GDP growth experienced smaller adverse effects from such policies.

More broadly, the role of behavioral responses has been emphasized by Goolsbee and Syverson (2021), who show that much of the decline in economic activity during the pandemic was driven by voluntary avoidance behavior rather than policy restrictions alone. This suggests that urban recovery dynamics reflect not only formal policy measures but also endogenous behavioral adjustments by firms and consumers.

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Our dataset includes a substantial number of businesses located in downtown areas of major cities, with a strong representation of service sectors. Differences between downtown districts and surrounding neighborhoods may generate heterogeneous recovery dynamics, making spatial variation within cities a key focus of this study.

2.1.2 Cross-country analysis

Drawing on the World Bank's extensive firm-level data collection, which includes the Business Pulse Survey (BPS) and the Enterprise Surveys (WBES) COVID-19 follow-ups, a series of studies provides critical insights into the pandemic's impact on firms across different time horizons and sample structures.

Apedo-Amah et al. (2020) offer a broad snapshot of the initial shock based on a massive cross-section of over 100,000 firms in 51 mainly low- and middle-income economies between April and August 2020. On average, 84% of firms reported sales declines of about 49%, with the largest drops observed in countries such as South Africa, Bangladesh, Nepal, Honduras, India, and Jordan. Tourism-related sectors (accommodation and food services) were disproportionately affected, and micro and small firms were significantly more likely to face liquidity shortages.

Extending this analysis, Constantinescu et al. (2025) construct a refined panel dataset across 61 countries by combining multiple waves of the BPS and the WBES COVID-19 follow-ups covering the period from April 2020 to September 2021. They show that digitalization and adaptability contributed to firm resilience over time, particularly among SMEs. Similarly, Muzi et al. (2023), drawing on World Bank firm survey data covering roughly 14,000–17,000 firms across 34 countries (primarily in Europe and Central Asia), show that more productive and longer-established firms were significantly more likely to survive the crisis. Survival rates were also higher among firms that had adopted digital tools or introduced new products prior to the pandemic, with these effects particularly pronounced for small businesses. Businesses facing heavier regulatory compliance burdens, by contrast, exhibited higher exit risks.

Amin et al. (2023) analyzed survey data from 5,197 firms (4,097 SMEs and 1,100 large firms) across 19 developing countries in four regions (Sub-Saharan Africa, Eastern Europe and Central Asia, Latin America and the Caribbean, and the Middle East and North Africa). The study found that SMEs were more severely affected by the pandemic, with an average sales decline of 34.8% compared to 22.6% for large firms, resulting in a 12.2 percentage-point gap. Decomposition analysis revealed that approximately 65% of this gap is explained by differences in pre-shock attributes, particularly lower pre-pandemic labor productivity and greater exposure to supply chain disruptions. These findings underscore the importance of initial endowments and preparedness in shaping resilience.

Bachas et al. (2025) use a balanced panel covering formal corporate taxpayers in six developing countries (Costa Rica, the Dominican Republic, Guatemala, Honduras, Ethiopia, and Uganda), based on full-population tax records for 2019–2020. Using administrative tax and VAT data, they simulate a three-month lockdown and compare predicted outcomes with realized results. They find that formal firms were more resilient than expected: the share of profitable firms declined by about 7 percentage points, while aggregate profits and tax revenues remained broadly stable, partly due to flexible input adjustments by large firms.

In addition to firm-level determinants, a growing body of research emphasizes the role of government support design in shaping business resilience. Comparative evidence from European countries shows that COVID-19 support programs were largely broad and easily accessible, such as wage subsidies and fixed-cost support, aimed

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at stabilizing firms and preserving employment in the short term (Van Helden et al., 2024).

While some cross-country findings are reflected in this study, our contribution lies in the broader scope of variables. Beyond SME characteristics and downtown location, we analyze 26 distinct factors, including governmental and non-governmental support, business model changes, and adaptation strategies.

2.1.3 Medium-term effects

While a substantial body of research has examined the immediate and short-term impacts of COVID-19 on businesses, relatively fewer studies have investigated its medium-term consequences. Literature on natural hazard recovery suggests that factors affecting business recovery can vary significantly through time (Watson et al., 2024). As the pandemic evolved, analytical attention increasingly shifted from the initial shock to the broader macroeconomic and geopolitical environment that followed. In particular, the recovery phase has been shaped not only by the lingering effects of COVID-19 but also by subsequent disruptive events, making it more difficult to disentangle pandemic-specific impacts from other structural shocks.

OECD (2023), drawing on the OECD–World Bank–Meta Future of Business Survey (March 2022), which covers roughly 10,000–15,000 SMEs (under 250 employees) across 34 OECD countries, and the OECD Timely Indicators of Entrepreneurship, shows that although firm creation rebounded strongly in 2021, new business entry slowed markedly in Q1–Q3 2022 following the outbreak of the war in Ukraine. At the same time, firm exits and bankruptcies rose sharply, reversing the unusually low levels observed during the pandemic. These trends have been partly attributed to the unwinding of pandemic-era support measures: some firms with borderline viability may have been able to continue operating temporarily due to extensive government support, while others accumulated debt through emergency loans but later faced repayment difficulties, contributing to a subsequent increase in business failures. More broadly, these developments reflect mounting pressures from the energy crisis, high inflation, tighter monetary policy, and the withdrawal of fiscal support, indicating that observed recovery patterns are the combined result of multiple overlapping shocks rather than COVID-19 alone.

Our business survey inevitably captures the combined effects of multiple economic shocks beyond COVID-19. Nevertheless, by employing an IPTW-based propensity score weighting approach, we aim to identify whether adaptation strategies and policy responses adopted during the pandemic help explain the current divergence in business performance.

2.2 Datasets

This study draws on the business survey covering 3,454 businesses across seven global regions, with Europe represented by the Netherlands (Amsterdam) and the EU excluding the Netherlands[2]. This section presents an overview of the survey dataset, with a focus on the key variables used in the analysis.

Fig. 1 presents the sectoral composition of the sample in each case study region, together with sample sizes and corresponding GDP structures. For the analysis, businesses are classified into ten broad industry sectors to

[2] A more detailed overview of the survey design and implementation will be provided at the DesignSafe site: https://www.designsafe-ci.org/ (under preparation).

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maintain balance across observations. We aggregate Agriculture with Mining and Manufacturing because they generally involve limited direct interaction with customers compared with service-oriented industries. Though this classification is less common in literature, it is also motivated by sample composition, as the number of observations in Agriculture (N = 24) and Mining (N = 12) is relatively small compared with Manufacturing (N = 262), and their individual shares in the overall sample are therefore limited.

GDP by sector data are compiled from multiple sources due to data availability constraints. While city-level data are used where possible, some cases include broader regional data[3]. In addition, there are classification constraints in GDP sector definitions. For instance, in South Africa, many personal service activities are categorized under "Other Services," which may affect comparability across regions. Based on observed sectoral GDP structures, substantial heterogeneity exists across case study regions, which may lead to diverse recovery patterns. In terms of regional coverage, the United States has the largest sample size (N = 893), followed by the European Union excluding the Netherlands (N = 676)[4] and Canada (N = 442).

While the core questionnaire design and data structure were consistent across all the cases, the distribution of sectoral shares varies substantially across case regions. Wholesale and Retail accounts for the largest share in Thailand, South Africa, and Japan, whereas Information and Communication is more prominent in the EU. Construction dominates in New Zealand, and the Professional, Technical, and Public Services sector represents a relatively large share in North America. Although this study ensures comparability across sectors and regions by aligning sample characteristics as closely as possible, observed differences in sectoral GDP structures across case study regions provide a valuable basis for interpreting recovery patterns at the city level.

The empirical strategy of this study combines pooled and case-specific analyses. Pooling data improves statistical power and helps identify general patterns, while case-specific analysis captures regional heterogeneity. This complementary approach enables a more comprehensive understanding of cross-regional similarities and differences in business recovery.

Fig. 2 plots the proportion of businesses that have not yet recovered from the impacts of COVID-19. At the end of the survey, more than 26.2% of businesses had not returned to their pre-pandemic sales levels, although substantial cross-country variation is observed. Thailand exhibits the slowest recovery, whereas South Africa shows relatively limited remaining effects of the pandemic.

These descriptive patterns provide insights that complement macroeconomic indicators. While aggregate data suggest that many regions had largely recovered by 2021, the survey results reveal persistent heterogeneity at the firm level. For example, although Thailand's GDP in 2022 exceeded its pre-pandemic level[5], a substantial share of businesses in Bangkok continues to report incomplete recovery. Similar contrasts between macro-level recovery and business-level outcomes are observed in other case study regions. These findings suggest that business-level data capture dimensions of recovery that are not fully reflected in aggregate economic indicators, offering a more nuanced understanding of post-pandemic recovery dynamics (e.g., Xiao, 2019).

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[3] Specifically, New Zealand is represented by the combined data of Auckland and Christchurch; the Netherlands by Amsterdam; Japan by Osaka; Thailand by Bangkok; South Africa by national-level data (see references); Canada by the combined data of Vancouver and Calgary; the EU (excluding the Netherlands) by aggregated GDP across 26 countries (see references); and the United States by the combined data of Los Angeles and Miami.

[4] The major countries are Germany (60.9%), followed by Hungary (11.5%), Austria (7.4%), and Belgium (5.7%).

[5] Thailand's GDP in 2022 reached 5,746,918 million baht, exceeding its pre-pandemic level of 5,711,599 million baht in 2019.

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A key reason why the impacts of COVID-19 appear to persist in the present survey data is the high prevalence of small-scale businesses in the sample. Indeed, 44.7% of businesses employ fewer than 20 workers. As documented in the existing literature (Bartik et al., 2020; Fairlie, 2020), smaller firms tend to exhibit lower resilience, contributing to slower recovery.

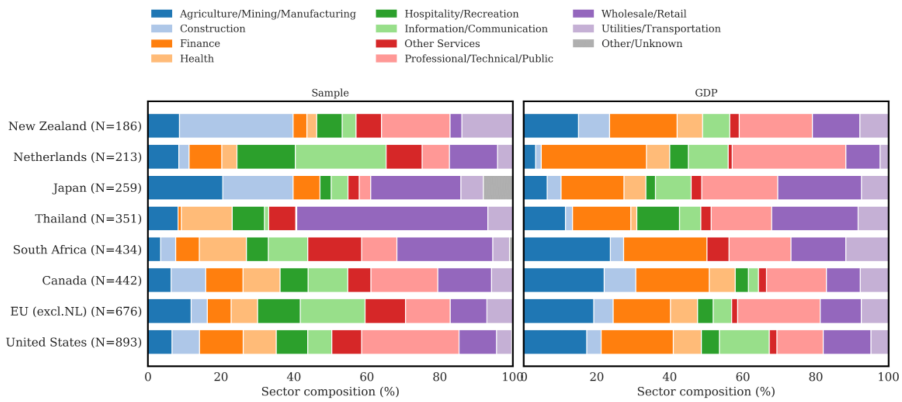

Figure 1. Comparison of sectoral composition between the survey sample and GDP across case regions.

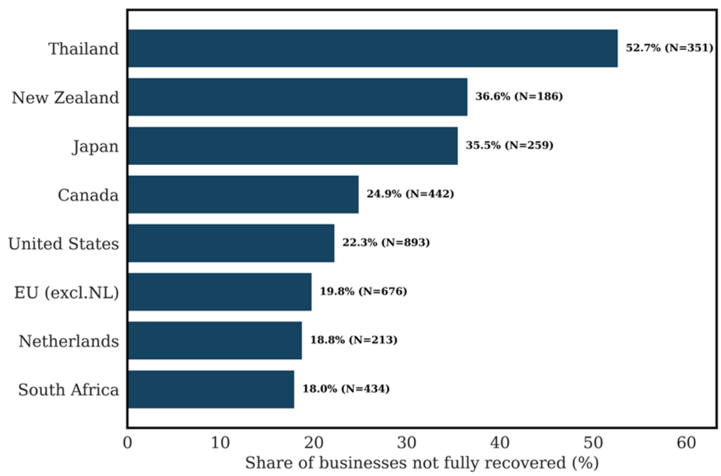

Figure 2. Share of businesses not fully recovered from COVID-19 across each case.

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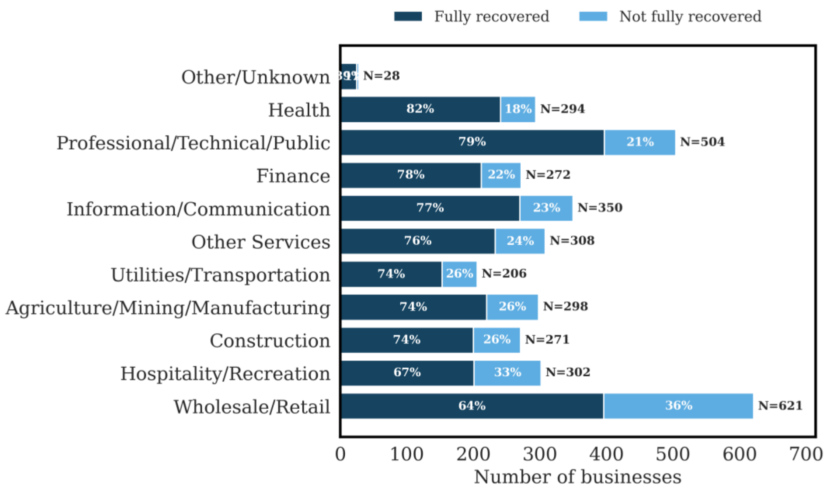

Figure 3. Sample sizes across sectors by recovery status.

Fig. 3 presents the number of observations and sales recovery status by sector. Wholesale/Retail accounts for the largest share and includes a high proportion of firms that have not fully recovered. Hospitality/Recreation also shows relatively slow recovery, reflecting its reliance on face-to-face interactions and human mobility. In contrast, Health Services exhibits the highest recovery rate, consistent with the essential nature of these activities. Professional/Technical/Public Services, Information/Communication, and Finance also show relatively strong recovery, partly due to their ability to operate online.

Table 1 summarizes the treatment (T), control (C), and the outcome (Y) variables. A total of 26 treatment variables capture differences in business characteristics, government support, financial conditions, funding sources, mentoring and training, and adaptation strategies. Their effects on the outcome variable (sales recovery level) are evaluated to conduct comparative business resilience and policy analysis.

In this study, the term "treatment" is used in a broad sense to encompass three distinct categories: (i) policy-related interventions (e.g., grants, loans, training), (ii) business-level characteristics (e.g., downtown location, female ownership), and (iii) endogenous business decisions implemented during the pandemic (e.g., staffing adjustments, digital technology adoption, and operational restructuring). While a unified estimation framework enhances comparability, these categories differ in their causal interpretation.

Policy variables approximate causal effects under selection-on-observables assumptions, whereas firm characteristics and business decisions should be interpreted as conditional associations. In particular, business decisions may reflect responses to declining performance, and reverse causality cannot be fully ruled out.

Given the presence of potential sample selection bias, the empirical design incorporates 21 control variables, primarily reflecting pre-determined firm characteristics. These controls are included to minimize observable differences between treated and untreated firms, thereby approximating a controlled comparison. This strategy aligns with the identification assumptions underlying inverse probability of treatment weighting (IPTW) and related doubly robust estimators.

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Some variables, such as female ownership, serve as treatment variables in certain specifications while functioning as control variables in others. This dual role reflects their substantive importance in assessing recovery differences, as well as their relevance as potential confounders in estimating other treatment effects. Controlling such variables is therefore necessary to mitigate bias when evaluating alternative treatment specifications.

In principle, it would also be possible to control firms' actions, such as the receipt of loans or grants, as additional control variables. However, these variables are potentially endogenous, as they could be jointly determined with pre-existing business characteristics and unobserved managerial decisions. Including them as controls would therefore risk conditioning on post-treatment variables, which could bias treatment effect estimates and complicate causal interpretation. Moreover, the inclusion of such variables would substantially increase multicollinearity among covariates, while also complicating interpretation. For these reasons, the baseline specifications prioritize pre-determined firm attributes as control variables.

The analysis also controls pandemic exposure using a composite measure of revenue loss during the worst period, combining the magnitude and duration of sales decline. This variable captures the intensity of the initial shock and allows comparison of recovery outcomes among firms with similar levels of impact.

Table 1. Variable definitions (T: treatment, C: control, Y: outcome).

Variable name	Type	Definition	Values
Business Characteristics			
Female-owned	T, C	Business owned by female owner(s).	[1 = female-owned (self-reported), 0 = Other]
Owned premises	T, C	Business owns the physical premises where operations are conducted.	[1 = business owns premises, 0 = rents/leases]
Downtown	T, C	Business operates in a downtown.	[1 = located in downtown, 0 = located outside downtown or location not applicable]
Home-based	T, C	Business operates from residential premises rather than dedicated commercial space.	[1 = home-based, 0 = other]
Franchise	T, C	Business operating under a franchise agreement.	[1 = franchisee, 0 = other]
Sole proprietorship	T, C	Business owned and operated by a single individual without formal incorporation.	[1= sole proprietorship, 0 = other]
Family-owned	T, C	Business controlled by members of the same family through majority ownership or management control.	[1 = family-owned, 0 = other]
Full-time employees: 1-4	T	Micro-enterprises with 1-4 full-time employees.	[1 = 1-4 employees, 0 = more than 4 employees]
Full-time employees: 1-9	T	Very small enterprises (1-9 full-time employees) distinguished from small-medium enterprises (≥10).	[1 = 1-9 employees, 0 = 10 or more employees]
Full-time employees: 1-19	T	Small firms with 1-19 full-time employees, distinguished from medium enterprises (≥20).	[1 = 1-19 employees, 0 = 20 or more employees]
Government Support (*during COVID-19 pandemic*)			
Wage subsidy	T	Receipt of government wage subsidy programs designed to preserve employment during revenue disruptions.	[1 = received, 0 = not received]
Other subsidies	T	Receipt of non-wage government support, including tax relief/deferment, rent or lease relief, debt repayment deferrals, or other subsidy instruments.	[1 = received, 0 = not received]
Any subsidies (at least one of available subsidies)	T	Indicator of participation in any government subsidy program, including wage subsidies or non-wage support.	[1 = received at least one subsidy, 0 = received none]
Financial conditions			
Debt increase	T	Increase in debt level during the pandemic relative to pre-crisis baseline.	[1 = debt level increased ("increased a lot" or "increased somewhat" on a

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Variable name	Type	Definition	Values
			5-point Likert scale), 0 = unchanged, decreased, or not applicable]
Cash decrease	T	Decline in cash reserves relative to pre-crisis baseline.	[1 = cash decreased ("decreased somewhat" or "decreased a lot" on a 5-point Likert scale), 0 = unchanged, increased, or not applicable]
Largest Source of Funding			
Government grants	T	Receipt of non-repayable government grants from federal, state, or local programs.	[1 = grants reported as largest source, 0 = otherwise]
Personal savings used	T	Use of owner's personal savings as the primary non-revenue funding source during the pandemic.	[1 = personal savings reported as largest source, 0 = other or none]
Government loans	T	Receipt of government-sponsored loan programs offering favorable terms relative to market rates.	[1 = government loan reported as largest non-revenue funding source, 0 = not received]
Private bank loans	T	Commercial bank financing obtained through traditional lending channels at market rates.	[1 = private bank loan reported as largest non-revenue funding source, 0 = not received]
Mentoring and Training			
Governmental (Gov.) mentoring/training	T	Participation in government-provided business mentoring or training services (e.g., marketing, financial management, operations).	[1 = participated, 0 = not participated]
Non-governmental (Non-gov.) mentoring/training	T	Participation in mentoring or training services provided by non-governmental organizations, private providers, or industry associations.	[1 = participated, 0 = not participated]
Business Adaptation			
Business adaptation support	T	Receipt of targeted support services facilitating pandemic adaptation, including assistance with applications, resource identification, business model transformation, digitization, or well-being support.	[1 = received, 0 = not received]
Staffing and operational changes	T	Implementation of workforce or operational adjustments in response to pandemic-related constraints or demand shifts.	[1 = changes implemented, 0 = not implemented]
Major business model changes	T	Fundamental restructuring of the firm's core value proposition, revenue model, or market positioning.	[1 = changes implemented, 0 = not implemented]
Digital technology	T	Accelerated adoption of digital technologies, including e-commerce, digital payments, remote work systems, CRM, or social media marketing.	[1 = investment implemented, 0 = maintained pre-pandemic level]
Other operational changes	T	Operational changes not captured by staffing, business model, or digital technology categories.	[1 = changes implemented, 0 = not implemented]
Control and Outcome			
Revenue loss (during worst period)	C	Revenue loss during the worst pandemic period, calculated as the product of revenue loss percentage and disruption duration (months).	[Formula: (100 - Impact) × Worst period duration. Duration mapping: 1=0.5, 2=2, 3=5, 4=9, 5=15, 6=24 months. Revenue mapping: 1=0%, 2=12%, 3=37%, 4=62%, 5=87%, 6=100%, 7=110%. Missing values imputed with median.]
Impact sources	C	Number of distinct pandemic impact sources affecting business operations, including supply chain disruptions, labor shortages, reduced customer demand, operational constraints due to health regulations, and compliance costs.	[Continuous, 0–5]
Pre-pandemic employment	C	Number of full-time employees before the pandemic calculated using the midpoint of each reported range. The highest category ("More than 500") is top-coded at 500.	[2.5 (1-4), 7 (5-9), 14.5(10-19), 34.5 (20-49), 74.5 (50-99), 174.5 (100-249), 374.5 (250-499), 500 (>500)]
Employment change	C	Change in full-time employment relative to the pre-pandemic baseline.	[Pre-pandemic employment – Current employment]
Business age	C	Years since establishment at current location	as of 2024
Sales recovery level	Y	Degree of sales recovery relative to pre-pandemic levels.	[Current sales as a percentage of pre-pandemic sales (>0%)]

Notes: nine sector dummy variables are additionally used as covariates.

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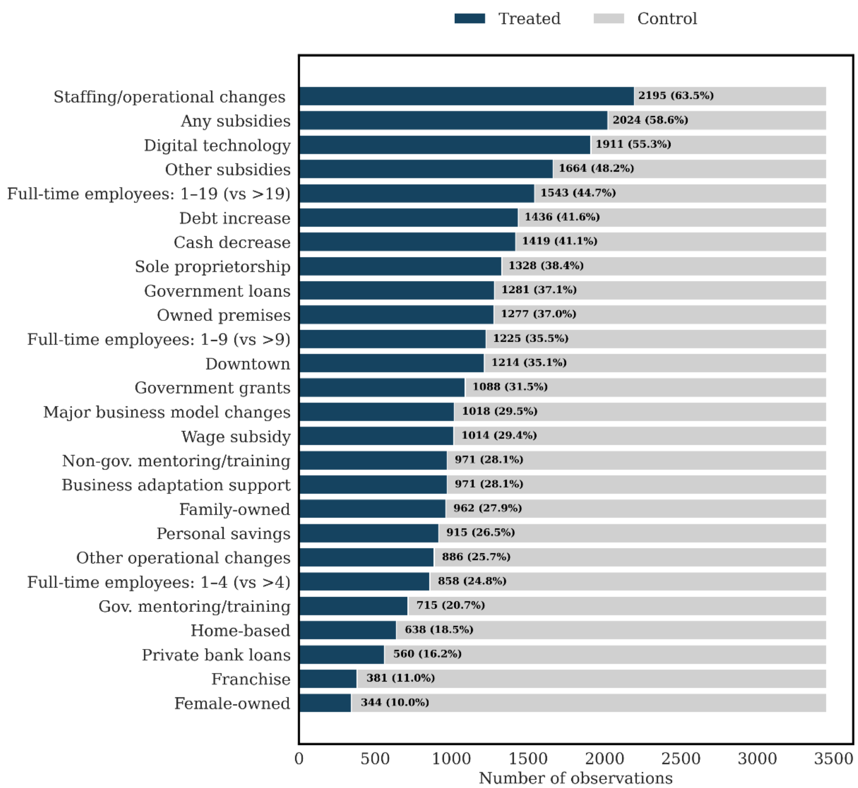

Figure 4. Share of treated units for each binary treatment variable.

Fig. 4 illustrates the presence or absence of firm attributes and actions corresponding to each of the 26 treatment variables. The most commonly reported action among businesses is *staffing and operational changes* (63.5%). This is followed by *any subsidies* (58.6%), *increased use of digital technology* (55.3%), and other subsidies (48.2%), which capture government subsidy programs excluding wage subsidies. These actions represent measures frequently observed during the COVID-19 pandemic.

While *major business model changes* (29.5%), *non-governmental mentoring or training* (28.1%), *business adaptation support* (28.1%), *other operational changes* (25.7%), and *governmental mentoring or training* (20.7%) were undertaken by a non-negligible share of firms, the number of firms using these measures remains relatively limited compared with the most prevalent actions.

With respect to financing sources, *government loans* (37.1%) constitute the largest reported funding source, followed by *government grants* (31.5%). A substantial proportion of businesses relied on *personal savings* (26.5%), whereas *private bank loans* were the least utilized source, reported by only 16.2% of firms.

Regarding firm characteristics, a large share of the sample consists of small-scale businesses, as indicated by the sole proprietorships (38.4%) as well as the high proportions of firms with *1–19 full-time employees* (44.7%). In contrast, the shares of *franchise businesses* (11.0%) and *female-owned businesses* (10.0%) are relatively small.

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For treatment variables with a limited number of treated observations, the full-sample analysis remains informative in assessing average effects; however, conducting disaggregated analyses by region or industry becomes challenging due to insufficient sample sizes.

3 Doubly robust estimator for average treatment effects on the treated (ATT)

The determinants of business recovery from the pandemic are highly multifaceted. In this study, we collect information on several dozen business-level characteristics, such as business location and age. Given this high dimensionality, applying a simple empirical strategy, such as a linear regression model that simultaneously includes all covariates, would be difficult and potentially unreliable.

To address this challenge, we adopt a quasi-experimental approach based on propensity score and conduct the analysis separately for each factor of interest. Specifically, we construct two statistically comparable groups and estimate the average effect of the presence of a given factor on post-pandemic business outcomes, approximating a balanced comparison between treated and untreated firms conditional on observed covariates.

Treatment effects are typically evaluated either as the Average Treatment Effect on the Treated (ATT), which focuses on treated firms and compares them with observationally similar control firms, or as the Average Treatment Effect (ATE), which extends the comparison to the entire population. In this study, because the number of treated observations is often limited, we focus on the ATT as our primary estimand.

As an indicator of business recovery, we use the level of sales recovery at the time of the survey, normalized such that pre-pandemic sales equal 100. Let Y denote the sales recovery level, and let T be a binary treatment indicator (T=1 for treated firms and T=0 for control firms). ATT is then defined as

$$\mathrm{ATT} = \mathrm{E}[Y(T=1) - Y(T=0) \mid T=1]. \quad (1)$$

As a more reliable approach to estimating the ATT (or ATE), the doubly robust estimator has been widely used in the literature. This method combines propensity score estimation with an outcome regression used to construct counterfactual outcomes. A key advantage of the doubly robust estimator is that it yields a consistent and unbiased estimate of the ATT (or ATE) as long as either the propensity score model or the outcome regression model is correctly specified (Scharfstein et al., 1999). Following Mercatanti and Li (2014), we describe the basic structure of the doubly robust estimator for the ATT as follows.

$$\widehat{\tau_{dr}^{ATT}} = \frac{1}{N_1}\sum_{i=1}^{N}\left[T_i\left(Y_i - \widehat{m_0}(\boldsymbol{X_i})\right) - (1-T_i)\frac{\hat{e}(X_i)}{1-\hat{e}(X_i)}\left(Y_i - \widehat{m_0}(\boldsymbol{X_i})\right)\right], \quad (2)$$

where the variables are defined as follows:

Y_i : Observed outcome for unit i (Sales recovery level).

$T_i \in 0,1$: Treatment indicator for each sample, where $T_i = 1$ denotes treated units.

$\boldsymbol{X_i}$: Vector of observed covariates for unit i.

$N_1 = \sum_{\mathrm{i}=1}^{\mathrm{N}} Z_i$: Number of treated units.

$\hat{\mathrm{e}}(\boldsymbol{X_i})$: Estimated propensity score.

$\widehat{\mathrm{m}_0}(\boldsymbol{X_i})$: Estimated outcome regression function for the control group, $\mathrm{E}[Y_i | T_i = 0, \boldsymbol{X_i}]$.

This framework corresponds to an ATT version of the Augmented Inverse Propensity Weighting estimator for the ATE (AIPW-ATE) introduced by Glynn and Quinn (2010). In Eq. (2), the second term inside the square brackets integrates propensity score weighting with the outcome regression. This structure yields the doubly robust property, whereby consistent estimation of the ATT is achieved provided that either the propensity score model is

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correctly specified or the outcome regression sufficiently accounts for residual confounding. The propensity score is defined as the probability of receiving treatment conditional on observed covariates:

$$e(\boldsymbol{X}_i) = P(T_i = 1|\boldsymbol{X}_i). \tag{3}$$

In this study, the propensity score is modeled using logistic regression, following Rosenbaum and Rubin (1983).

The improvement of covariate balance is assessed using standardized mean difference (SMD), which measures differences in covariate distributions between treated and control groups before and after the IPTW. The SMD is defined as

$$\mathrm{SMD} = \frac{\bar{X}_{T=1} - \bar{X}_{T=0}}{\sqrt{\frac{\sigma^2_{T=1} - \sigma^2_{T=0}}{2}}}. \tag{4}$$

Here,

$$\bar{X}_{T=k} = \frac{1}{n_{T=k}} \sum_{i:T_i=k} X_i,\ \ \sigma^2_{T=k} = \frac{1}{n_{T=k}-1} \sum_{i:T_i=\mathrm{k}} (X_i - \bar{X}_{T=k})^2,$$

where $k \in \{0,1\}$ denotes the treatment status. Smaller absolute values of the SMD indicate better covariate balance between the treated and control groups.

To construct counterfactual outcomes, we specify an outcome regression for untreated units as

$$Y_i = m_0(\boldsymbol{X_i}) + \varepsilon_i, \quad E[\varepsilon_i|\boldsymbol{X_i}, T_i = 0] = 0. \tag{5}$$

Here, $\boldsymbol{m_0}(\boldsymbol{X_i})$ denotes the conditional mean outcome for untreated units as a function of the covariate vector $\boldsymbol{X}_i$. The error term ε_i captures unobserved determinants of the outcome.

4 Analysis

4.1 Covariate balance after IPTW adjustment

In this study, treatment effects are analyzed for 26 treatment specifications using both the full pooled dataset and subsamples stratified by region and industry. Given the large number of cases, it is impractical to report covariate balance diagnostics for all specifications. Therefore, for illustrative purposes, we present the extent of covariate balance improvement for the pooled sample.

The set of explanatory variables X_i used in the propensity score model includes case-region and sector dummy variables, resulting in a maximum of 26 covariates. Because some covariates are also used as treatment variables in specific specifications, the number of covariates is reduced to 25 in those cases to avoid mechanical overlap.

Fig. 5 illustrates the improvement in covariate balance, measured by SMDs, between treated and control groups before and after the application of IPTW. Although SMDs are computed for all 26 treatment cases, we report only the specification exhibiting the smallest improvement in balance. Even in this least favorable case, IPTW substantially reduces imbalance, with most covariates falling below the commonly used threshold of 0.1 (Normand et al., 2001), indicating adequate covariate balance.

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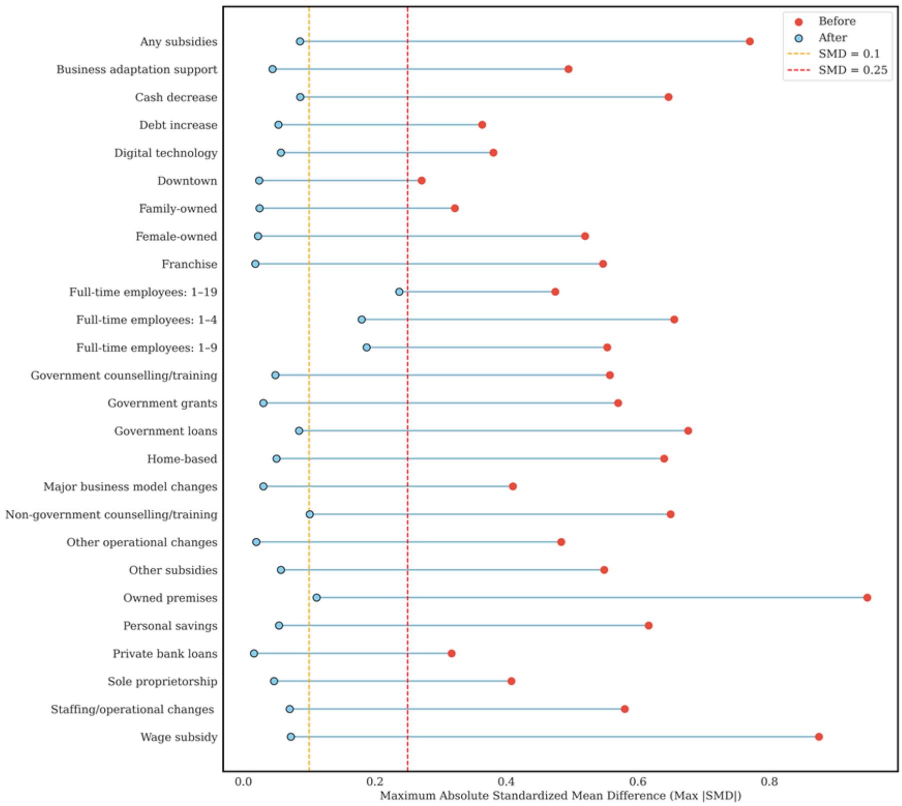

Figure 5. Improvements in maximum absolute standardized mean difference (Max |SMD|) after inverse probability of treatment weighting (IPTW) for each treatment specification.

4.2 Outcome regression results

In the outcome regression specified in Eq. (5), the same set of covariates used in the propensity score model is included. The baseline specification relies on a full model that incorporates all available covariates to estimate the expected value of the outcome variable, although not all coefficients are statistically significant.

Table 2 reports the average estimated regression coefficients across the 25 or 26 treatment specifications and the number of cases in which each covariate is statistically significant at the 5% level. Variables that are consistently significant across all specifications include *Business age*, *Employment change*, *Revenue loss (during the worst period)*, the *South Africa* case dummy, and *Owned premises*.

The negative coefficient for Business age indicates that younger firms tend to recover more quickly. In addition, firms that own their premises also tend to recover faster. In contrast, firms that experienced larger revenue losses during the most severe phase of the pandemic show slower recovery.

The negative coefficient on *Employment change* reflects the tendency for establishments that reduced their workforce to display slower recovery. This relationship may operate in both directions: on the one hand, insufficient labor recovery may constrain firms' ability to restore sales; on the other hand, firms experiencing slower sales recovery may be less able or willing to rehire workers. As such, the observed association likely

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captures a mutually reinforcing dynamic between employment and sales recovery rather than a strictly one-directional effect.

The consistently positive coefficient for *South Africa* indicates relatively faster recovery in that case region, potentially reflecting institutional flexibility or adaptive economic structures not fully captured by the survey data. According to the City of Cape Town (2023), the recovery of air connectivity ("Air Access") and the growth of the IT and BPO sectors have been key factors enabling Cape Town to outperform other major cities such as Johannesburg.

A second group of influential variables includes *Thailand, Pre-pandemic employment, Home-based* (business), and *Downtown.* In contrast to *South Africa*, *Thailand* exhibits systematically slower recovery. This pattern cannot be fully explained by industry composition, as sector dummy variables are not statistically significant in the outcome regression, nor is it adequately captured by firm size as measured by pre-pandemic employment. These findings suggest the presence of broader regional factors influencing recovery dynamics in Thailand.

Why, then, do sector effects not appear statistically significant in the regression results? Although *Wholesale/Retai*l and *Hospitality/Recreation* sectors appear particularly affected in **Fig. 2**, it does not emerge as a significant determinant of recovery once other controls are introduced. One possible explanation is that sector-specific differences are already absorbed by the *Revenue loss* variable, which incorporates both the duration and severity of the pandemic shock[6]. In other words, the most severely affected sectors may be identified indirectly through shock intensity rather than through sector indicators themselves.

Additional results indicate two distinct patterns across location and business type. First, firms located in downtown (central business district) areas exhibit, on average, a 3.70 percentage point higher recovery rate compared with those in surrounding (non-downtown) areas. Second, home-based businesses show a 4.41 percentage point lower recovery rate than those operating in dedicated commercial spaces. A more rigorous assessment of effect magnitudes is provided in the subsequent doubly robust ATT analysis, which adjusts for covariate imbalance.

The R^2 of the outcome regression is modest (0.19–0.23), which is expected given the substantial heterogeneity in medium-term business recovery across firms and countries. As noted by Austin (2011), goodness-of-fit measures such as R^2 do not provide a test of whether the outcome regression model is correctly specified or whether systematic differences between treated and untreated units have been eliminated.

In principle, the analysis could alternatively be conducted using a reduced specification, in which explanatory variables are selected based on information criteria such as the Akaike Information Criterion (AIC). However, as discussed above, the outcome regression in the present study is not intended for prediction in new data, but rather serves as a component for bias adjustment within the doubly robust framework. Variables with relatively small individual contributions tend to offset each other across covariates, and as a result, the estimated ATT remains qualitatively similar across both the full and reduced model specifications. Accordingly, model specification is guided by considerations of confounding control rather than predictive performance.

[6] Empirically, we also compared alternative specifications using duration-only and severity-only measures. The composite indicator consistently showed better model performance in terms of AIC, suggesting that it captures relevant variation more effectively.

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4.3 Estimated ATTs by treatment for pooled, case-specific, and sector-specific samples

This subsection presents the estimated ATT results for the pooled dataset as well as the case-specific and sector-specific samples. To enhance robustness, ATT estimates are not reported when either the treated or control group contains fewer than 30 observations, although the propensity score literature does not prescribe a fixed minimum sample size. As shown in **Figs. 7** and **8**, some estimates still exhibit wide 95% confidence intervals, particularly in subsamples with limited observations, such as female-owned businesses. As a result, certain treatment variables cannot be evaluated reliably in some case-specific or sector-specific analyses.

The pooled sample allows most treatment variables to be examined and provides a broad overview of the results. At the same time, because pooled estimates are more strongly influenced by regions or sectors with larger sample sizes, they may mask important heterogeneity across subsamples. Therefore, while **Fig. 6** presents the pooled results as the main benchmark, we also examine the case-specific results (**Fig. 7**) and sector-specific results (**Fig. 8**) to assess whether the pooled patterns are driven by particular regions or industries.

Table 2. Mean coefficient values and significant cases in outcome regressions.

Variable Name	Mean coefficient	significant cases
Const	112.06	26
Business age	-0.18	26
Employment change	-0.08	26
Revenue loss (during worst period)	-0.02	26
Case: South Africa	28.96	26
Owned premises	8.08	25
Case: Thailand	-14.66	22
Pre-pandemic employment	0.02	18
Home-based	-4.41	16
Downtown	3.70	15
Case: United States	5.66	12
Case: New Zealand	-6.57	9
Female-owned	-3.63	5
Impact sources	0.17	4
Case: EU (excl.NL)	3.27	4
Sector: Finance	-3.97	3
Sector: Other Services	5.23	3
Case: Netherlands	2.66	3
Franchise	-0.05	2
Case: Japan	-3.75	2
Sector: Information/Communication	-2.01	1
Sector: Hospitality/Recreation	-3.34	1
Sector: Professional/Technical/Public	-0.47	1
Sector: Utilities/Transportation	-1.88	1
Sector: Wholesale/Retail	-2.67	1
Sector: Construction	-2.34	0
Sector: Health	0.02	0

4.3.1 Firm characteristics

Turning to firm characteristics, *Owned premises* (+6.6) is consistently associated with faster recovery. Sector-specific effects are particularly strong in Hospitality/Recreation (+12.2) and Professional/Technical/Public services (+10.6), where ownership may reduce fixed costs during disruptions and enhance financial stability

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(Ivanov and Faulkner, 2021).

Downtown (*location*) (+4.7) contributes positively to recovery, especially in Canada (+8.9) and the United States (+5.9), with positive average effects observed in the EU as well. While stronger effects might be expected in Wholesale/Retail or Hospitality/Recreation, larger effects are instead observed in Information/Communication (+11.5) and Health Services (+12.7). This may reflect faster restoration of demand in sectors where proximity facilitates access to communication infrastructure, professional services, or medical care.

By contrast, sectors such as Wholesale/Retail and Hospitality/Recreation may have been more exposed to persistent behavioral changes following the pandemic, including increased reliance on online shopping and a sustained reduction in in-person dining and leisure activities. Such structural shifts in consumer behavior may have dampened the advantages traditionally associated with downtown locations in these sectors.

Family-owned (businesses) exhibit the third-largest positive effect (+3.5). The effect is particularly pronounced in Canada (+8.9) and in infrastructure-related industries such as Utilities/Transportation (+12.5) and Construction (+10.5). This finding contrasts with Clemente-Almendros et al. (2023), suggesting that family ownership may enable flexible labor adjustments and support faster recovery.

In contrast, recovery delays are clearly observed among *Home-based businesses* (-6.8) and small enterprises with fewer than 20 employees (below -10.7), with recovery declining as firm size decreases. *Female-owned* businesses also show a negative effect (-4.1), although not statistically significant at the 5% level. In OECD (2023), among the businesses surveyed, 12% of women-led firms currently had a bank loan compared to 20% of male-led firms. Complementary research finds that female-owned firms face 50% more rejections in applications for traditional trade finance than male-owned businesses.

These patterns are broadly consistent across regions, with one notable exception in the Netherlands, where firms with 10–19 employees recover faster than larger firms. Given that the 1–19 category shows a positive effect while the 1–9 category is negative, this suggests potential nonlinear firm-size dynamics. One possible explanation is that policy measures in this context were more effectively targeted toward smaller firms, but were less effective for the smallest firms. Dutch Committee for Entrepreneurship (2021) notes that "In terms of turnover development, compared to large companies, the SME sector managed to make it through the pandemic relatively well."

In the United States, sole proprietorships (+6.1) exhibit a positive effect, indicating that institutional or regulatory differences may influence recovery trajectories. While such firms are often considered vulnerable, this result suggests a more nuanced pattern. One possible explanation is greater agility, as sole proprietors can make rapid decisions without complex internal coordination (Hannan and Freeman, 1984). In addition, this category may capture entrepreneurial firms with strong adaptive capacity, which has also been seen in the hazards literature (Alesch et al., 2001; Grube and Storr, 2018).

4.3.2 Financial support and funding

Regarding financial treatments, *Private bank loans* (+3.8) and *Government loans* (+3.2) meet the 5% significance threshold in the pooled analysis. In contrast, firms receiving subsidies exhibit relatively limited recovery gains (< +2.5), and those identifying *Government grants* as their primary funding source show a negative average effect (-1.4). One possible explanation is that grants are often distributed broadly, regardless of firm performance, and have been linked to the persistence of "zombie" firms. Alternatively, grants may represent a

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smaller share of firms' total financing needs compared to loans, which are often provided in larger amounts given their repayable nature, particularly in contexts such as the United States. As a result, grants alone may be insufficient to support substantial recovery, especially for firms facing prolonged or severe disruption.

In contrast, loans typically involve stricter screening, potentially signaling expectations of future viability and allocating larger amounts of capital to firms with stronger recovery prospects. However, evidence from Flanders complicates this interpretation: Konings et al. (2023), analyzing 26,324 firms, find that subsidy recipients experienced a statistically significant 4–5% increase in labor productivity relative to comparable non-recipient applicants, although this advantage had dissipated by the end of 2021.

It is important to distinguish between two types of private bank lending: government-guaranteed loans and non-guaranteed (conventional) loans. Altavilla et al. (2025), analyzing lending by 1,206 banks to 2,639,651 firms across four European countries (Germany, Italy, Spain, and France), find that banks providing guaranteed loans reduced their existing non-guaranteed lending to the same firms by more than 30%, suggesting substantial substitution. This effect was particularly pronounced for firms in sectors most affected by the pandemic, for smaller and riskier firms, and among financially stronger banks. Overall, the results imply that during the COVID-19 crisis, private bank lending may have been more selectively allocated toward more profitable or lower-risk firms, potentially contributing to heterogeneous recovery outcomes.

Note that heterogeneity is evident in our study. In Canada, subsidies outperform loans, and in sectors such as Information/Communication and Professional/Technical/Public services, subsidy effects are comparatively strong. In fact, based on comprehensive administrative data covering the entire universe of Canadian firms (over 16 million observations) from 2002 to 2022, Amundsen (2025) concludes that pandemic support programs did not cause an increase in zombie firms. Contrary to widespread concerns, the share of zombie firms in Canada actually declined from 5.6% in 2019 to 4.4% in 2022. The extensive dataset demonstrates that government support effectively helped viable firms survive and recover rather than artificially sustaining unviable companies.

In the United States, wage subsidies appear to have supported recovery, which contrasts with the short-term findings of Granja et al. (2022). Using loan-level data for all PPP loans (over $500 billion) matched with high-frequency employment data for small and mid-sized firms (≤500 employees) during April–August 2020, they show that program targeting was weak and heavily mediated by banks. The short- and medium-term employment effects were modest relative to the program's size, as many firms used funds for fixed payments and precautionary savings rather than immediate job retention.

Finally, *Debt increase* (-10.2) and *Cash decrease* (-24.2) produce expected signs. While both variables are likely correlated, reductions in cash reserves exert a substantially larger negative effect on recovery. Whereas debt accumulation was widespread during the pandemic, depletion of operating liquidity may have led to downsizing or layoffs, thereby slowing recovery. The interaction between these financial stress indicators warrants further structural modeling.

4.3.3 Non-financial supports and adaptation actions

We first examine business-level adaptation actions. In the pooled sample (**Fig. 6**), *non-governmental mentoring/training* shows the largest positive effect, increasing recovery levels by 9.2 percentage points (+9.2) relative to pre-pandemic sales (normalized to 100%). The effectiveness of such non-financial measures, rather than

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direct financial transfers, is notable and less emphasized in prior literature. Case-specific analysis (**Fig. 7**) indicates significant positive effects in Canada (+14.4), South Africa (+9.4), and the United States (+6.66, p=0.072). In other regions, limited sample sizes restrict statistical comparison. Sectoral results show strong effects in Wholesale/Retail (+10.5), Finance (+15.5), and Other Services (+15.7), with particularly pronounced contributions in the United States.

The effect of non-governmental support may partly reflect mechanisms similar to those associated with business networking. Business networks are important not only for exchanging resources and information but also for fostering trust and providing emotional support among firms (Saezow and Sukhabot, 2025; Koporcic et al., 2025).

Governmental mentoring/training ranks third in overall impact (+5.6). Again, non-financial instruments appear more effective than direct financial assistance such as loans or grants. Regionally, significant effects are observed only in the United States (+7.0). Canada shows weaker effects compared with non-governmental training, while Thailand displays negative average estimates. Sectoral patterns suggest positive effects in service-oriented industries, including Wholesale/Retail (+9.6), Finance (+8.1, p = 0.13), and Other Services (+12.5, p = 0.23).

Major business model change (+3.8) also contributes positively to recovery. It is particularly influential in New Zealand, and positive tendencies are observed in South Africa and the Netherlands. Although not statistically significant at the 5% level in all cases, positive effects are detected in Agriculture/Mining/Manufacturing, Hospitality/Recreation, and Finance.

In contrast, *increased use of digital technology* (+0.2) shows limited overall effectiveness, although it plays a more important role in specific contexts. In Japan, digitalization ranks among the strongest contributors to recovery, and sector-specific results show significant effects in Health Services (+11.8), where remote services and telemedicine may have supported faster recovery. Evidence from previous studies is also mixed. Muzi et al. (2023), based on a large cross-country survey, show that the positive effect of digitalization on firm survival is primarily driven by small firms (5–49 employees). When restricting the sample to medium and large firms (50+ employees), digitalization, such as website ownership, does not have a statistically significant impact on survival. By comparison, Constantinescu et al. (2025) find that the positive effects of digital adoption persisted over time, remaining significant at least until September 2021. These contrasting findings suggest that longer-term impacts should be examined more carefully, taking into account not only the presence of digital tools but also the intensity and quality of digital use.

Finally, *Staffing and operational changes* (-3.9) show significantly negative associations, consistent with the earlier findings in Section 4.2. The negative effects are especially significant in Construction and Information/Communication (-10.0), which suggest that staffing adjustments may reflect reactive cost-cutting in response to declining performance rather than proactive adaptation. A similar interpretation applies to *Other operational changes* (-4.6), particularly in Information/Communication (-10.0), where delayed recovery may have prompted businesses to adopt such measures.

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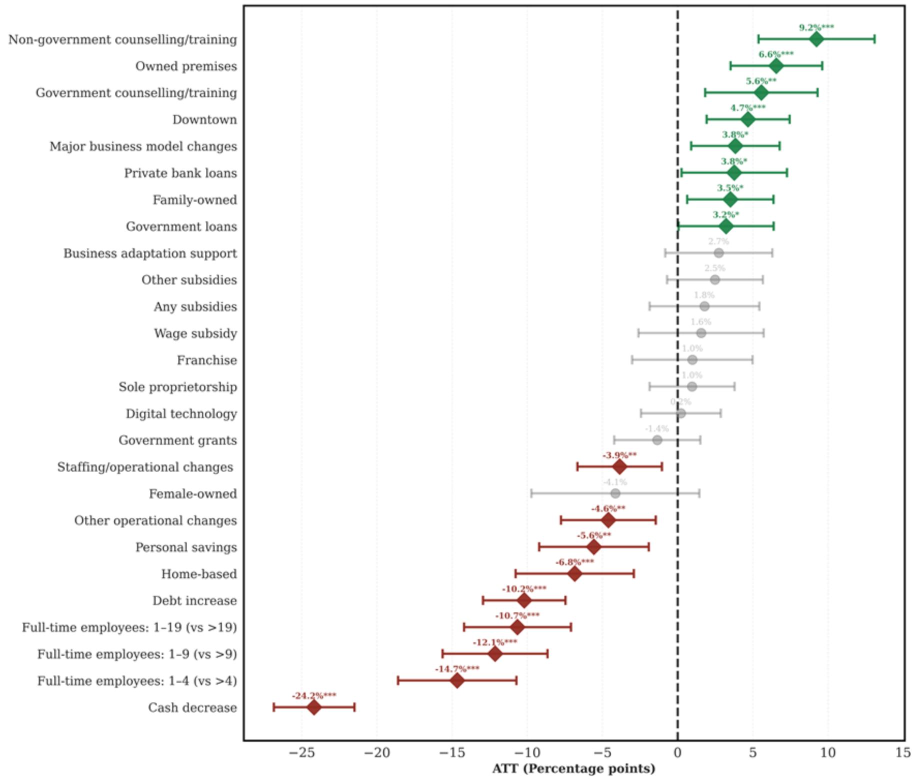

Figure 6. Average treatment effects on sales recovery for pooled data

(Asterisks indicate statistical significance at the 5 %, 1 %, and 0.1 % levels, respectively.)

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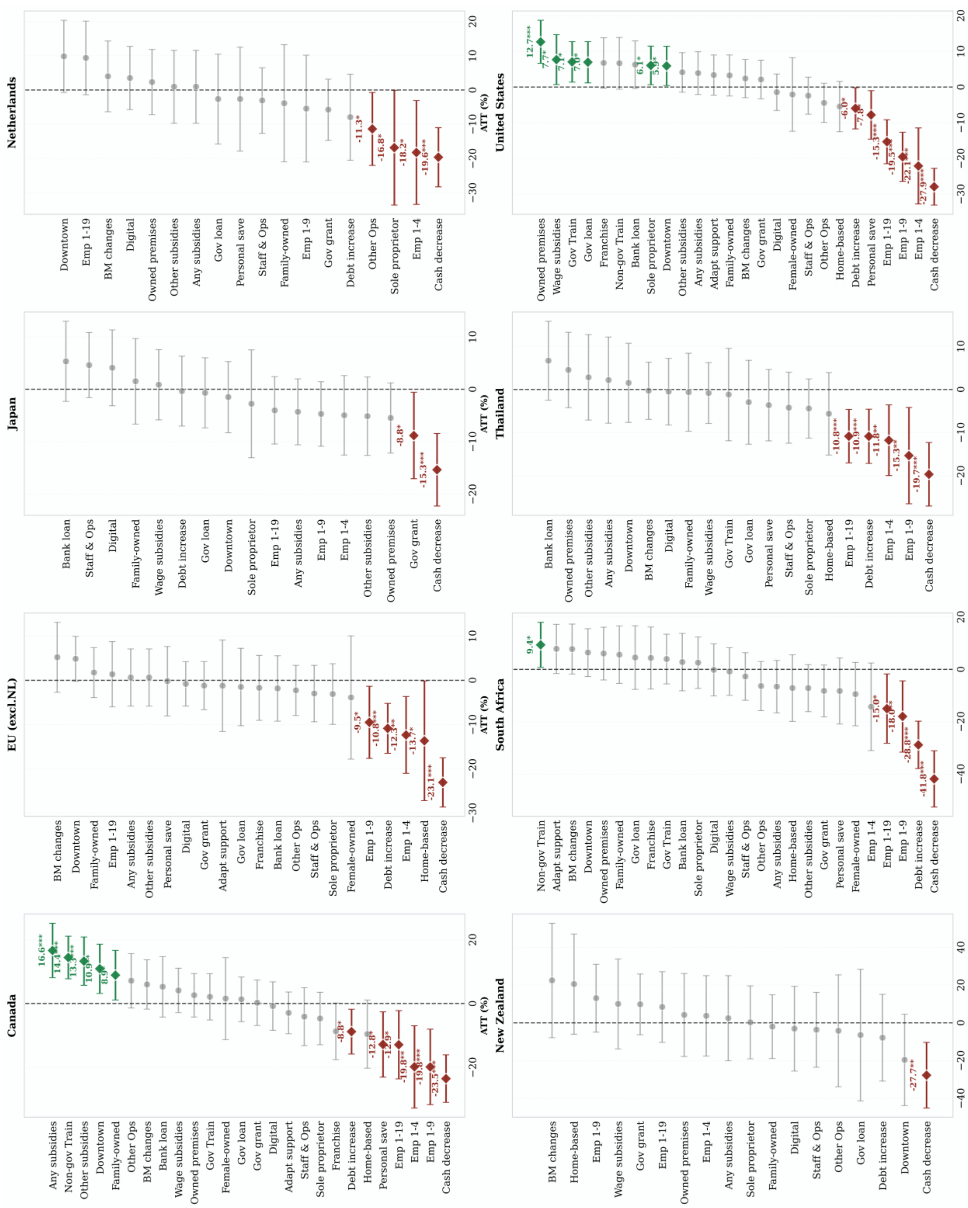

Figure 7. Treatment effects on sales recovery level in each case region

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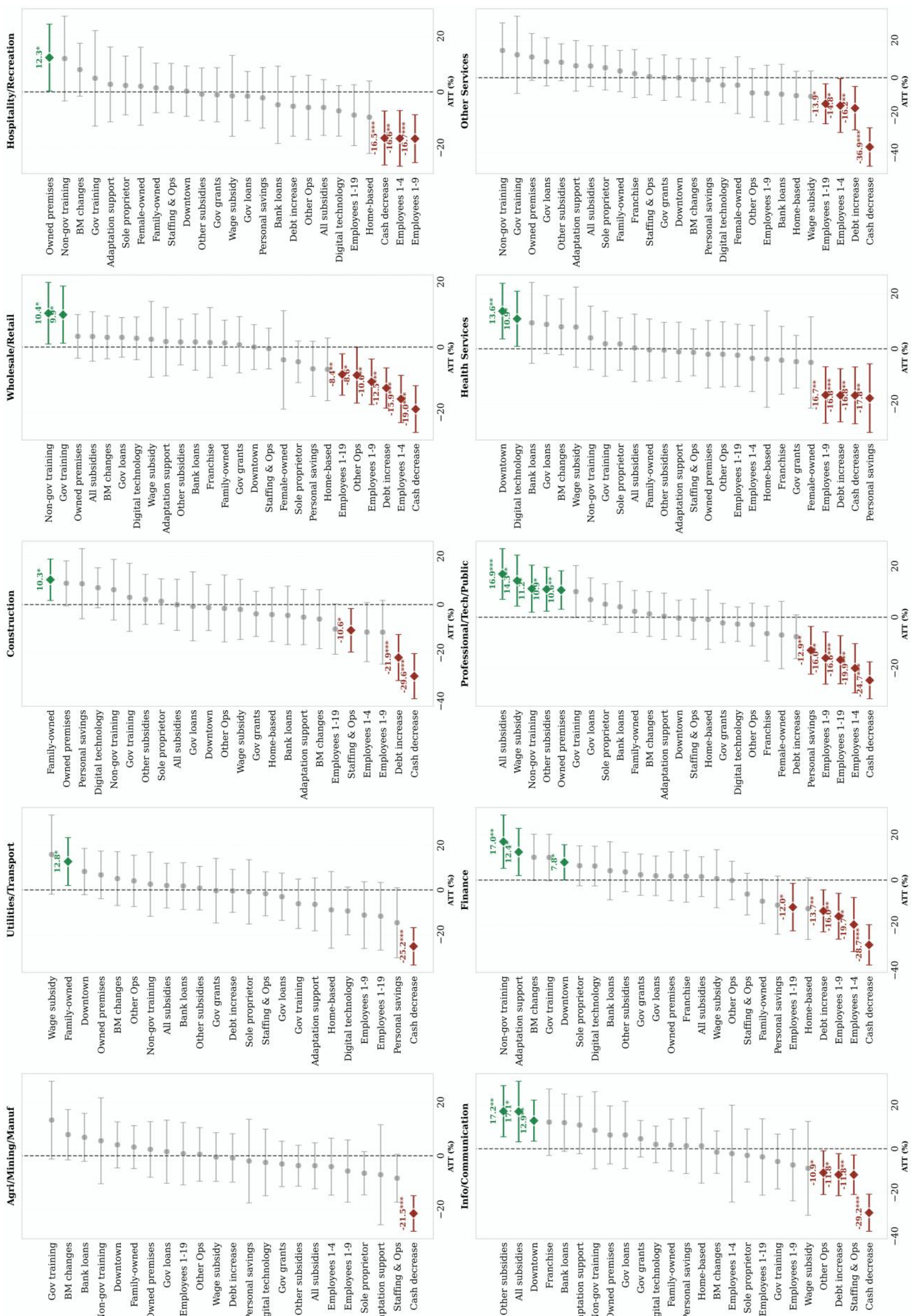

Figure 8. Treatment effects on sales recovery level in each sector.

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4.4 Relationships among treatment variables

As noted above, several treatment variables are correlated with one another. Examining these interrelationships helps provide a more nuanced interpretation of the results in Section 4.3. To explore the overall structure of these associations, **Fig. 9** displays Pearson correlation coefficients with absolute values exceeding 0.2. Positive correlations are shown in blue and negative correlations in red, with line thickness proportional to the magnitude of the correlation.

Consistent with the findings in Section 4.3, *Non-governmental mentoring/training* (*Non-gov Train*) occupies a central position in the network. It exhibits strong positive correlations with *Governmental mentoring/training* (*Gov Train*) and *Business adaptation support* (*Adapt Supp*), suggesting complementarities among these support mechanisms.

Non-governmental mentoring/training is also positively associated with *Government loans* (*Gov loan*) and Subsidies (*Wage subsid* and *Other subsid*)[7], indicating that advisory support may be linked to access to financial assistance. Firms exposed to a larger number of *Impact sources* are more likely to receive subsidies, and to implement *Staffing and operational changes* (*Staff & Ops*), reflecting the severity of the shock they experienced.

Negative correlations are observed between *Non-governmental mentoring/training* and the small-business indicators *Emp 1–4*, *Emp 1–9*, and *Emp 1–19*, suggesting that smaller firms are less likely to receive such support. These firms also tend to rely more heavily on personal funding, exhibit weaker digital adoption, experience larger reductions in cash reserves, and accumulate more debt. In addition, younger businesses appear more likely to experience declines in cash reserves.

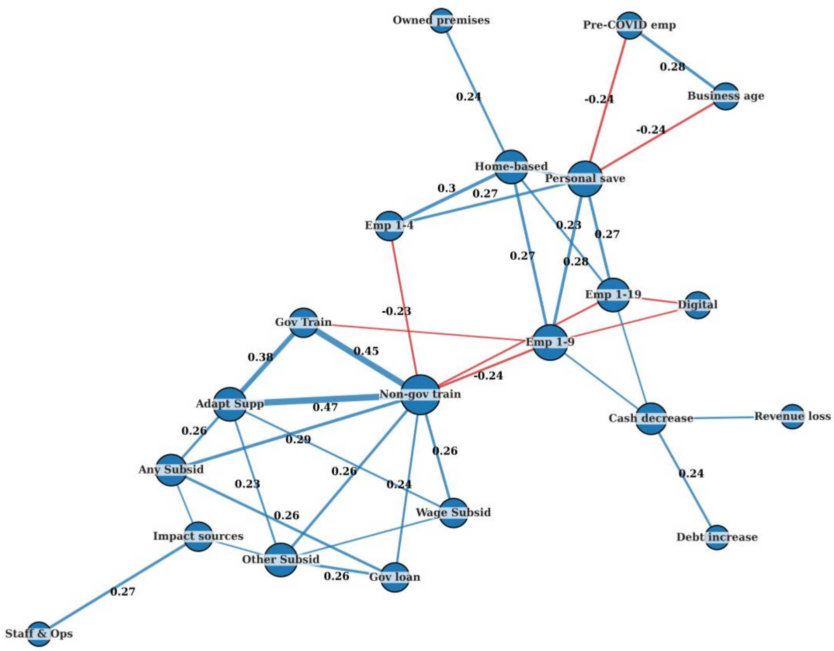

Figure 9. Correlation diagram for treatment variables.

5 Discussion and conclusions

Taking 2020 as the peak of the COVID-19 crisis, this study examines business recovery four to five years later using survey

[7] Recall that "*Any Subsid(ies)*" is a binary indicator taking the value of one if either *Wage Subsid* or *Other Subsid* is received.

data from 3,454 firms across seven regions. Although macroeconomic indicators suggest that the overall impact of the pandemic has largely subsided, 26.2% of firms in our sample had not yet returned to pre-pandemic sales levels, underscoring the persistence of recovery gaps in the medium term. The primary objective of this study has been to identify region-specific patterns of persistent recovery gaps and to examine the mechanisms underlying these differences.

Some findings align with prior expectations, while others diverge. Importantly, variation is observed not only in the direction but also in the magnitude of effects. The large-scale international dataset enhances the credibility of the analysis by enabling consistent comparisons across diverse institutional and economic contexts, while also capturing heterogeneity shaped by local conditions.

One of the most notable findings is the strong effect of *non-governmental mentoring and training support* (ATT = +9.2). These forms of support appear to complement business adaptation measures and facilitate access to financial resources. Although *private bank loans* (+3.8) and *other subsidies* (+2.5) also show positive associations, their effects are smaller and do not fully explain the magnitude observed for non-governmental training. This suggests that advisory support may promote productivity improvements, inter-firm collaboration, or strategic adjustments not directly captured by the explanatory variables.

In contrast, small firms (1–19 employees) are less likely to receive such support and more likely to rely on personal financing, contributing to slower recovery. Their lower levels of digital adoption further highlight the need for targeted support mechanisms to prevent isolation of small enterprises.

The relatively strong recovery observed among family-owned businesses was not necessarily expected, given that such firms are often small in scale and potentially more vulnerable to prolonged shocks. However, this finding is consistent with emerging evidence suggesting greater resilience among family firms, potentially reflecting their organizational flexibility and capacity for rapid adaptation (Prasad and Roy, 2026; Kodama et al., 2024; Soler-Porta and Rodríguez, 2024).

Other results, such as stronger recovery among firms receiving loans rather than grants, firms located in downtown areas, firms owning their premises rather than renting, and male-owned firms, are broadly consistent with prior hypotheses. However, these patterns are not uniform across regions or industries, and effect magnitudes vary substantially. This heterogeneity highlights the need for region- and sector-specific policy design.

For example, downtown location is strongly associated with higher sales recovery in the Information/Communication and Health Services sectors, whereas no significant effect is observed in Wholesale/Retail or Hospitality/Recreation. These findings suggest that the effectiveness of location-based advantages depends on sectoral characteristics. Sectors such as Information/Communication and Health Services may benefit from urban agglomeration effects, including access to advanced digital infrastructure and concentrated service demand, while Wholesale/Retail and Hospitality/Recreation appear less sensitive to downtown location and may require alternative forms of targeted support.

Regarding financial conditions, increases in debt (-10.2) and decreases in cash reserves (–24.2) display expected signs, although cash depletion appears more strongly associated with slower recovery. While debt accumulation was widespread during the pandemic, liquidity shortages may have triggered downsizing and prolonged recovery.

Although this study focuses on the COVID-19 pandemic, the findings also have relevance for business support following natural-hazard events. Disasters such as floods, earthquakes, wildfires, and storms often disrupt firms through revenue losses, liquidity constraints, supply-chain interruptions, labor shortages, and shifts in local demand, and previous disaster research has shown that business recovery trajectories differ substantially by firm size, ownership, sector, and location (Alesch et al., 2001; Marshall et al., 2015; Chang et al., 2022; Helgeson et al., 2022). Our results suggest that post-disaster assistance should not rely solely on grants or loans, but should combine financial instruments with advisory, mentoring, and training support that helps firms access resources, adapt operations, and rebuild networks. The observed vulnerability of small firms and the heterogeneity across regions and sectors further imply that natural-hazard recovery programs should be tailored to local business ecosystems rather than implemented as uniform short-term relief packages. In this sense, evidence from medium-term business recovery after COVID-19 can inform the design of more targeted business-continuity and recovery support for

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future natural-hazard and compound-shock events.

Finally, several limitations should be acknowledged. Although IPTW combined with outcome regression enhances robustness, constructing perfectly comparable treated and control groups remains challenging given the complexity of recovery determinants. The broad definition of "treatment," encompassing policy interventions, firm characteristics, and endogenous decisions, implies important differences in causal interpretation. In particular, business decisions may reflect responses to declining performance, and reverse causality cannot be fully addressed. As such, ATT estimates for these variables should be interpreted as conditional associations rather than causal effects.

Despite the relatively large sample sizes in several regions, sectoral and firm-level imbalances persist, and the cross-sectional design further limits causal inference. While the doubly robust IPTW framework reduces confounding from observable covariates, unobserved heterogeneity may still affect the results. Future research could benefit from more targeted sampling strategies or sector-focused designs, as well as longitudinal data that better capture dynamic adjustment processes. In addition, explicitly modeling the sequencing of decisions and outcomes would help disentangle causal pathways and strengthen policy-relevant interpretations. These limitations are particularly relevant when interpreting implications for urban economic resilience and long-term sustainability, where dynamic adjustment processes and spatial heterogeneity play a central role.

Overall, this international collaborative effort provides quantitative evidence on medium-term business recovery following COVID-19 while also identifying important directions for future research and policy development. More comprehensive assessment and long-term monitoring of business recovery are required to inform the refined design of pandemic response policies and broader urban resilience strategies, particularly as the effects of continuous consumer behavioral changes and accumulated debt obligations may continue to shape firm performance in the coming years.

Code availability

The code used for the statistical analyses is available from the corresponding author upon reasonable request. The code is not publicly archived at this stage because it depends on project-specific data harmonization and variable-coding procedures for an individual-level, multi-country survey dataset.

Data availability

The full individual-level survey dataset is not publicly available because the surveys were conducted in each case-study region under region-specific ethical approvals, data-use conditions, and confidentiality requirements. The dataset contains confidential business-level survey responses and cannot be released publicly without approval from the responsible research teams. However, details of the survey design and implementation will be provided through the DesignSafe site: https://www.designsafe-ci.org/ (under preparation).

Author contributions

All authors contributed to investigation and resources. Yoshio Kajitani led the conceptualization and methodology, conducted the formal analysis, developed the software, validated the results, prepared the visualizations, curated the data, acquired funding, supervised the work, and wrote the original draft. Maria Watson contributed to data curation, funding acquisition, supervision, and writing – review and editing. Stephanie E. Chang contributed to funding acquisition, project administration, and writing – review and editing. Elsamari Botha contributed to data curation and writing – review and editing. Sophie L. Buijs, Sahar Derakhshan, and Juri Kim contributed to data curation. Siriporn Darnkachatarn contributed to data curation, formal analysis, software, validation, and visualization. Marleen de Ruiter, Sanna Malinen, and Bernard Walker contributed to supervision and writing – review and editing. All authors read and approved the manuscript.

Competing interests

The authors declare that they have no conflict of interest.

Special issue statement

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