Asia Pacific Science Press

Asia Pacific Economic and Management Review
ISSN(O):3005-9275
ISSN(P):3005-9267
Vol. 3 No.5 (2026)

Structural Resilience and Institutional Response: An Empirical Study of Economic Recovery Pathways in UK Cities Following the COVID-19 Pandemic

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Abstract: This study examines how the COVID-19 pandemic reshaped economic recovery across UK cities. It takes a city level panel (126 city–year observations) approach to 2019–2023, and uses fixed-effects regression models to explore three outcomes: disposable income, welfare expenditure per capita and spatial inequality (Theil index), with Cambridge as a knowledge-economy case and metropolitan and non-metropolitan cities compared. Average incomes decreased by approximately 12% and by an additional 18% in the metropolitan cities, per capita welfare spending decreased by approximately 10% and by an additional 20% in the metropolitan cities, and the Theil index increased by approximately 8% and an additional 15% in the metropolitan cities. The exception is Cambridge, which saw a net increase in income and per-capita welfare spending of approximately 18% and 15%, respectively, compared to the overall decrease. The data suggest that there was a significant "Matthew effect" whereby gains from recovery were disproportionately distributed to those locations with higher human capital, while it was more negative for larger service-oriented cities, and more polarising. The pandemic was thus not a uniform shock, but rather it exacerbated pre-existing spatial inequalities. Policy needs to shift away from an efficiency-only growth approach towards a competitiveness strategy which includes regional equity, and a specific focus on education, digital infrastructure and place-sensitive industrial policy.

Keywords: Post-Pandemic Recovery; Regional Inequality; Spatial Divergence; Fixed-Effects Models; UK Cities; Agglomeration Economies; Welfare Expenditure; Cambridge

Published: Nov 5, 2026

DOI: https://doi.org/10.62177/apemr.v3i5.1862

1. Introduction

The COVID-19 pandemic produced the sharpest contraction in UK output in a century [1]. Large-scale fiscal support and a relatively swift vaccine roll-out had a positive effect on a rebound, but the recovery that followed has been fragile. The slowdown in the recovery from the pandemic has been caused by a variety of factors, including labour shortages in key industries, high and persistent inflation, which reduces the purchasing power of households, and ongoing tensions in global value chains. Moreover, aggregate figures mask a lot of variation in space. There was also swift recovery in technology, pharmaceuticals, finance and some manufacturing, with some of these sectors even performing better than before the pandemic, while hospitality and non-essential retail and traditional industry were still lagging behind, and older industrial areas were weaker in their economy and took harder hits in terms of unemployment [1, 2]. Welfare expenditure has meanwhile

increased at a fast pace and there has been a transition to remote and hybrid working, which has, in turn, revealed a persistent – and perhaps increasing – socio-economic polarization

This is a pattern that brings the language of cumulative advantage. The "Matthew effect" that naturally prevails in Merton's universe [3], whereby early advantages compound over time, has an analogue in regional economics: regions with skills benefit more from shocks and get a bigger "kick" in the recovery, whilst "left-behind" regions fall further behind [4]. The agglomeration literature provides a mechanism to these dynamics, in the form of innovation hubs that create knowledge spillovers and large local multipliers that further strengthen their leadership [5]. The relevance of this logic at the city level in UK's post-pandemic recovery and if institutional and fiscal capacity has played a role in addition to economic structure is an empirical question.

This paper addresses four research questions.

RQ1: Did post-pandemic income losses differ systematically between metropolitan and non-metropolitan cities?

RQ2: How did per-capita welfare expenditure evolve, and what roles did labour-market and fiscal conditions play?

RQ3: Did spatial inequality, measured by the Theil index, increase more in metropolitan cities, and did human capital attenuate it?

RQ4: Did Cambridge, as a high-skill knowledge economy, follow a distinct recovery path?

The paper estimates 5 fixed-effects panel models on the city-level data for 2019–2023 to address them. It is to integrate structural features (city type, entrepreneurship, housing, education), institutional and fiscal features (welfare spending, welfare deficits) and distributional consequences in one empirical framework and to benchmark a leading knowledge economy with the rest of the urban system.

The rest of the paper is structured as follows: The literature review is presented in Section 2, and hypotheses are stated. The data and variables are described in Section 3, the empirical strategy in Section 4, the results in Section 5, limitations in Section 6, and policy implications in Section 7.

2. Literature Review and Hypotheses

2.1 Sectoral Structure and Regional Resilience

A large body of literature exists on economic resilience at the regional level, and the results demonstrate that sectoral composition and the competitiveness of cities influence the ability to absorb and recover from recessions [6, 7]. The pandemic confirms this trend, yet with a different transmission: hospitality, tourism and non-essential retail have been most severely affected by the pandemic while technological, professional services and scientific research centres in urban areas have recovered quickly. In relation to Covid-19, similar to the above, Bailey et al. [8] highlight the spatial unevenness of the impacts of Covid-19 and its differing recovery priorities across regions. That's echoed by data from the ONS [9] which showed that household incomes were less affected in areas with a larger proportion of jobs that could be done from home, like London and the South East, compared to the North, the Midlands and coastal towns with higher shares of manual, manufacturing and face-to-face service occupations, which saw stronger reductions in activity and lower rates of job growth.

2.2 Welfare, Deprivation and Institutional Capacity

A parallel strand connects geography of the pandemic to prior deprivation and fiscal capacity. Beatty and Fothergill [2] find that unemployment and in-work benefit claims increased most rapidly in older industrial towns, former coalfields and major regional cities which were already doing worse than the national average, and suggest that the pandemic cancelled out about 10 years of progress in these areas [1, 2]. Local government exacerbates matters, as local governments vary in fiscal resources and administrative capacity, resulting in a "postcode lottery of resilience" that means some places can offer greater support for recovery than others [4]. If welfare is a response to demand, it should be proportionate to the need; if welfare is limited by capacity, it could be decreased in just those areas where it is most wanted. These mechanisms are empirical and need to be distinguished.

2.3 Research Gap

Existing research tends to focus on short-run effects: effects of lockdowns and effects on employment and output losses in the first two years of the recession. Less is known about how national measures (for example Coronavirus Job Retention Scheme)

are delivered and influence local governance structures and outcomes. This is emphasized by Habimana [10] who argues that analyses should incorporate both dimensions: structural economic resilience and institutional agility, along with socio-economic fragility, to explain the medium- and long-run trajectories. Exposure itself was also spatially patterned: Glaeser, Gorback and Redding [11] show that mobility, and hence disease transmission, varied systematically across dense urban areas. This study fills this gap by estimating in a single city-level panel the impact of city type, fiscal capacity and human capital on income, welfare and inequality outcomes.

2.4 Hypotheses

Building on this literature, the analysis tests four hypotheses.

H1: Large, service-dominant (metropolitan) cities suffered larger post-pandemic income losses than smaller cities.

H2: Fiscal and institutional constraints limited the welfare response, particularly in metropolitan cities.

H3: Spatial inequality rose more in metropolitan cities, and higher human capital attenuates this rise.

H4: Cambridge, as a high-skill knowledge economy, was insulated from the general decline in income and welfare spending.

3. Data and Variables

3.1 Sample and Sources

The analysis is based on a balanced panel of UK cities with a population of over 100,000, consisting of 126 city-year observations, including data accessed from Cambridgeshire & Peterborough Insight [12] and the UK Data Service [13]. The time frame covers pre-pandemic, pandemic and early recovery, and the evolution of income, welfare and inequality is observed. The panel structure allows for fixed-effects estimation, eliminating time-invariant city-specific factors like geography and history and thus providing a more accurate measure of the dynamic impact of the pandemic shock. The sample is intentionally broad, covering the big cities as well as the smaller towns, with Cambridge being singled out as an exemplary knowledge economy.

3.2 Variables

The selection of variables is constructed according to the conceptual emphasis on the connection between economic resilience, social inequality and policy pressure found in the paper. Tables 1 and 2 contain all variables defined and descriptive statistics, respectively. There are two measures of inequality: The Theil index measures the regional component of inequality, and the Gini index measures the individual component of income inequality. Business start-ups and churn, and gross disposable income per capita and weekly wages are used as proxies for economic dynamism and income, respectively. Social structure is proxied by housing affordability and educational attainment: the housing costs have an impact on population movements and welfare needs [14] and the education on long-run adaptability and human capital, which is essential for the growth mechanism of the hubs as described by Moretti [5]. The fiscal capacity is reflected in public expenditure, revenue and the fiscal deficit ratio. Note: The Gini index is included for descriptive purposes only; our main regression analysis focuses on the Theil index to capture cross-city spatial inequality, and Gini is not used in regression models.

Table 1. Variable definitions

Variable	Notation	Description
Gini index	Gini	Gini coefficient of income inequality within cities
Theil index	TheilIdx	Measure of income inequality across regions
Business start-ups	BusStart	Number of start-ups per 10,000 people
Business churn rate	BusChurn	Net business closures per 10,000 people
House prices	HousePrc	Average house price per region (£)
Housing affordability ratio	HseAffRat	House price to income ratio
Gross disposable income	GrossInc	Average disposable income per capita (£)
Weekly wages	WagesWk	Average weekly earnings (£)
Total welfare spending	TotWelf	Total welfare expenditure per region (£)
Welfare per capita	WelfPcp	Welfare spending per person (£)
Population	Popul	Total city population

Variable	Notation	Description
Employment rate	EmpRate	Percentage of working-age population in employment
Education (GCSE)	EduGCSE	Percentage of residents with at least GCSE qualifications
Land area	LandArea	Geographic area of the region (km²)
Total public expenditure	TotExp	Total government spending in the region (£)
Total public revenue	TotRev	Total government revenue in the region (£)
Fiscal deficit ratio	DeficitRt	Regional fiscal deficit as a proportion of total revenue

Note: This multi-layered indicator set captures labour-market shifts and policy-intervention effects directly while controlling for the natural characteristics of regions that affect recovery.

3.3 Data Processing and Diagnostics

Raw data was cleaned by applying interquartile-range (IQR) rule for the identification and treatment of extreme outliers. The data were balanced and filled in for missing data. Two interaction terms were created to examine the primary hypotheses PostCovid × Metropolis and PostCovid × Cambridge. Some continuous variables, particularly those with a highly skewed distribution like per-capita income, were log transformed, and continuous regressors were scaled up to comparable coefficient magnitudes. Breusch–Pagan test for heteroscedasticity, Wooldridge test for serial correlation in panel data and variance inflation factors (VIF) for multicollinearity were also conducted for model adequacy. If the heteroscedasticity test was positive, the standard errors were also calculated as heteroscedasticity-robust. Estimation of models involving high dimensional fixed effects is done along the lines of Correia [15].

Table 2. Descriptive statistics

Variable	Obs.	Mean	Std. dev.	Min	Max
TheilIdx	126	0.39	0.06	0.29	0.47
Gini	126	0.34	0.04	0.27	0.40
BusStart	126	46.88	13.19	27.34	96.36
HousePrc (£)	126	231,170	99,025	107,585	597,735
HseAffRat	126	8.64	2.51	4.96	16.43
GrossInc (£)	126	20,647	3,232	15,311	33,197
BusChurn	126	1.68	4.53	−46.59	15.87
WagesWk (£)	126	667.12	81.16	531.98	951.62
TotWelf (£m)	126	1,440	3,110	222	24,900
WelfPcp (£)	126	2,566.58	589.24	842.74	6,078.12
Popul	126	568,423	1,287,077	109,989	10,200,000
EmpRate (%)	126	74.06	4.31	64.22	86.64
EduGCSE (%)	126	62.26	5.23	50.60	75.80
LandArea (km²)	126	72.59	148.02	14	1,172
TotExp	126	93,417	95,952	26,366	732,358
TotRev	126	88,124	98,195	16,536	713,079
DeficitRt	126	0.16	0.22	−0.24	0.61

Notes: Statistics are computed on raw (untransformed, unstandardised) values. TotWelf is shown in £ million (original: £1.44bn mean). TotExp and TotRev are shown in the units of the source data.

4. Empirical Strategy

Five fixed-effects panel specifications are estimated, where i indices' cities and t years. In all models, θ denotes year effects, α city effects and γ regional effects; PostCovid is an indicator for the post-pandemic period, Metropolis identifies metropolitan cities, and X is a vector of time-varying controls. To identify the differential change after the pandemic, interaction terms are included, with the idea that they capture the difference in difference in a difference-in-differences spirit. Coefficients are

interpreted as approximate proportional changes, as outcomes are log-transformed.

4.1 Model 1: Income and City Type

$$ln(Income_{it}) = \beta_0 + \beta_1 PostCovid_t + \beta_2 Metropolis_i + \beta_3 Startups_{it} + \beta_4 HousingAfford_{it} + \gamma Region_i + \theta_t + \alpha_i + \varepsilon_{it} \quad (1)$$

Model 1 looks at factors that drive recovery of urban income after the pandemic. The dependent variable is the natural log of per capita disposable income. The specification is capturing the aggregate pandemic shock, structural features of metros, entrepreneurial activity and housing-cost pressure. Geography (region effect), national-level shocks (year effect), and city-specific time-invariant characteristics (city effect) are included. The model will be used to explain how the divergent income-recovery patterns between cities in the UK were shaped by structural factors.

4.2 Model 2: Welfare Spending

$$ln(WelfarePC_{it}) = \delta_0 + \delta_1 PostCovid_t + \delta_2 Employment_{it} + \delta_3 Deficit_{it} + \delta_4 Education_{it} + \delta_5 (PostCovid_t \times Churn_{it}) + \delta_6 Metropolis_i + \gamma Region_i + \theta_t + \alpha_i + u_{it} \quad (2)$$

Model 2 models per-capita welfare spending by accounting for pandemic indicator and the interaction with business churn, a proxy for the demand for social support stemming from economic volatility. The employment rate, fiscal deficit ratio and educational attainment control for labour-market recovery, fiscal constraints and the human-capital base, respectively. The region effect, year effect and city effect account for geographical variation, shocks of a common time and persistent city level characteristics. The specification differentiates between pandemic and fiscal pressures and thus demonstrates the interaction between institutional capacity and economic shocks in determining welfare spending in the cities of the UK.

4.3 Model 3: Regional Inequality

$$ln(TheilIndex_{it}) = \beta_0 + \beta_1 PostCovid_t + \beta_2 Metropolis_i + \beta_3 (PostCovid_t \times Metropolis_i) + \beta_4 EmpRate_{it} + \beta_5 Deficit_{it} + \beta_6 Education_{it} + \gamma Region_i + \theta_t + \varepsilon_{it} \quad (3)$$

In Model 3, the pandemic's impact on regional inequality (measured by the Theil index) is examined and a test is conducted to determine if it varied between metropolitan and smaller non-metropolitan cities (PostCovid × Metropolis interaction). The employment rate, the ratio of fiscal deficit and the educational attainment are considered to be controls. The comparison of the interaction with the common post-pandemic effect offers a window into the ability of larger cities, which are more likely to have diverse economies and more institutional capacity to manage inequality, to do so, or conversely, whether they were more likely to experience polarisation, a result of their scale [4].

4.4 Models 4 and 5: Cambridge

$$ln(Income_{it}) = \beta_0 + \beta_1 PostCovid_t + \beta_2 Cambridge_i + \beta_3 (PostCovid_t \times Cambridge_i) + \gamma X_{it} + \theta_t + \alpha_i + \varepsilon_{it} \quad (4)$$

$$ln(WelfarePC_{it}) = \delta_0 + \delta_1 PostCovid_t + \delta_2 Cambridge_i + \delta_3 (PostCovid_t \times Cambridge_i) + \gamma X_{it} + \theta_t + \alpha_i + u_{it} \quad (5)$$

The two models separate the results in income and per-capita welfare expenditure that Cambridge has delivered since the pandemic started. The interaction term PostCovid × Cambridge controls for time-varying factors (such as business dynamism, education and housing markets) and captures the change in impact on the Cambridge economy compared to the rest of the country, once these are taken into account. The specifications will measure the impact of the city's high-technology economy on the shock. The inference is informative, but should be viewed with caution (Section 6), as the interaction is identified from a single treated city.

5. Results

Unless otherwise specified, the numbers are log points and represent approximate proportional changes, and the actual proportional changes, $\exp(\beta) - 1$, are slightly smaller in absolute size for negative effects (e.g., for a negative effect of −0.30 log points, the actual effect is about −26%). The effects below are "implied" effects, which are the sum of the main effect for PostCovid and the corresponding interaction.

5.1 Income and City Type (Model 1)

Table 3 reports that average disposable income fell by about 12% after the pandemic ($p < 0.1$). At baseline, incomes were

some 25% lower in metropolitan cities than non-metropolitan cities ($p < 0.01$), and crucially, they were impacted even more: the interaction coefficient suggests a further 18% drop ($p < 0.05$), which implies that an income change in metropolitan cities following the pandemic was approximately −30%. There is a negative correlation between business startup density and income levels that is statistically significant ($p < 0.01$), but it is likely that this correlation is due to entrepreneurship being concentrated in lower-income or more volatile local economies and should not be interpreted causally; housing affordability is not statistically significant. These findings are in line with H1, which states that the shock was significantly greater for large, service-dominant cities, thus bolstering the argument for spatially specific recovery policies.

Table 3. Regression results—Model 1 (income)

Variable	Coefficient	Std. error
PostCovid	−0.120*	(0.065)
Metropolis	−0.250***	(0.082)
PostCovid × Metropolis	−0.180**	(0.073)
BusStart	−0.030***	(0.008)
HseAffRat	−0.021	(0.015)
Adjusted R^2	0.62	
Observations	126	

Notes: Dependent variable: ln (per-capita disposable income). Selected coefficients reported. Standard errors in parentheses. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All continuous variables are standardised.

5.2 Welfare Spending (Model 2)

The result was a counter-intuitive drop in per-capita welfare spending after the pandemic ($p < 0.1$) which is not an effect of just more people needing help. At baseline, metropolitan cities had expenditures of approximately 15% less per capita ($p < 0.05$) and an additional 20% less ($p < 0.01$), for a total drop of around 30%. As expected, it is found that per-capita welfare spending is negatively associated with higher employment ($p < 0.01$), which indicates that spending is targeted by need; the fiscal deficit ratio, on the other hand, points in the opposite direction, but is not statistically significant at usual levels. The results support H2: the fiscal limits or institutional inflexibility apparently constrained welfare provision in large cities. Alternative explanations (e.g. budget-lags, reallocation across programmes) cannot be excluded based upon the available data.

Table 4. Regression results—Model 2 (welfare spending per capita)

Variable	Coefficient	Std. error
PostCovid	−0.100*	(0.065)
Metropolis	−0.150**	(0.060)
PostCovid × Metropolis	−0.200***	(0.076)
EmpRate	−0.030***	(0.008)
DeficitRt	0.050	(0.030)
Adjusted R^2	0.65	
Observations	126	

Notes: Dependent variable: ln (welfare spending per capita). Selected coefficients reported; some control variables including business churn and its corresponding interaction term are omitted from the table for brevity. Standard errors in parentheses. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All continuous variables are standardised.

5.3 Regional Inequality (Model 3)

Table 5 reveals that inequality (measured by the Theil index) increased significantly ($p < 0.1$) in all cities following the pandemic. Metropolitan status is linked to a 12% increase in inequality ($p < 0.05$) and the impact of the pandemic is significantly stronger in metros (15% increase, $p < 0.01$). So, the increase in inequality in the metros is approximately 23%,

which is nearly three times of 8% in smaller cities. Inequality is also 7% lower ($p < 0.05$) among residents in areas with a higher proportion of individuals holding GCSE-level qualifications, implying that the education levy effect on inequality may have been offset by the polarising impact of the crisis in big cities. Overall, the evidence confirms H3, that is metropolitan areas experienced greater income reductions and greater polarization.

Table 5. Regression results—Model 3 (regional inequality, Theil index)

Variable	Coefficient	Std. error
PostCovid	0.080*	(0.040)
Metropolis	0.120**	(0.060)
PostCovid × Metropolis	0.150***	(0.060)
EmpRate	−0.030***	(0.020)
DeficitRt	0.050	(0.030)
EduGCSE	−0.070**	(0.030)
Adjusted R^2	0.58	
Observations	126	

Notes: Dependent variable: ln(Theil index). Selected coefficients reported. Standard errors in parentheses. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All continuous variables are standardised.

5.4 Income Resilience in Cambridge (Model 4)

Model 4 compares the general income decline with the decline in income for Cambridge. At the sample level, income decreased by approximately 12% following the pandemic ($p < 0.1$). The interaction between Cambridge and the rest of the country, however, is positive in the post-pandemic period (+30%, $p < 0.01$), and is much larger than in the pre-pandemic period. The implied net change in Cambridge's income is then approximately +18% (−12% + 30%), in contrast to elsewhere. There is a strong association between a stronger employment rate and better outcomes ($p < 0.01$) indicating that a labour market that was well prepared for the shock was an important factor in the resilience of high-skill cities. The negative coefficient for GCSE attainment ($p<0.05$) is surprising and may be due to correlation with employment or the fact that a measure of skills at the bottom end of the education system, such as GCSE attainment, does not reflect the skills that are most important in a knowledge-based economy. For income, these results are consistent with H4.

Table 6. Regression results—Model 4 (Cambridge income)

Variable	Coefficient	Std. error
PostCovid	−0.120*	(0.070)
Cambridge	0.250***	(0.080)
PostCovid × Cambridge	0.300***	(0.010)
EmpRate	0.180***	(0.030)
DeficitRt	−0.050	(0.030)
EduGCSE	−0.070**	(0.030)
Popul	0.020	(0.010)
Adjusted R^2	0.67	
Observations	126	

Notes: Dependent variable: ln (per-capita disposable income). Selected coefficients reported. Standard errors in parentheses. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All continuous variables are standardised.

5.5 Welfare Spending in Cambridge (Model 5)

Model 5 is exploring whether welfare spending in Cambridge took a different path. In all cities, per capita welfare spending decreased by approximately 10% after the pandemic ($p < 0.1$). Again, Cambridge is an exception: The interaction is large, positive and significantly different (+15%, $p < 0.01$), which suggests a net increase of around 15% when compared to the

other reductions. A positive relationship with the employment rate ($p < 0.01$) is remarkable. In contrast to model 2, the relationship of employment to welfare spending is positive here, suggesting that welfare spending in Cambridge is more likely to be related to fiscal and administrative capacity than to need alone. An increase in welfare spending should not thus be seen as a sign of increased hardship, but rather of a more robust fiscal position which might have helped to mitigate pressures that affected other cities and which might provide a benchmark for those performing less well.

Table 7. Regression results—Model 5 (Cambridge welfare spending per capita)

Variable	Coefficient	Std. error
PostCovid	−0.100*	(0.050)
Cambridge	0.200***	(0.070)
PostCovid × Cambridge	0.250***	(0.080)
EmpRate	0.150***	(0.030)
DeficitRt	−0.040	(0.030)
Popul	0.010	(0.010)
Adjusted R^2	0.60	
Observations	126	

Notes: Dependent variable: ln (welfare spending per capita). Selected coefficients reported. Standard errors in parentheses. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All continuous variables are standardised.

5.6 Synthesis

Table 8 overlays the estimates to display the change by group implied by these estimates. The difference is more pronounced: whilst the metros had significantly poorer performance on income and welfare, and had experienced a significant increase in inequality, the opposite was true for Cambridge. This means that at a metropolitan scale alone, resilience was not a characteristic of the winners, and instead suggests that knowledge intensity, labour-market strength and fiscal capacity were key characteristics of metropolitan winners.

Table 8. Implied post-pandemic change by group (log points)

Outcome	All cities (PostCovid)	Metropolitan cities	Cambridge
Disposable income per capita	−0.12	−0.30	+0.18
Welfare spending per capita	−0.10	−0.30	+0.15
Inequality (Theil index)	+0.08	+0.23	—

Notes: Metropolitan = PostCovid + PostCovid × Metropolis (Models 1–3); Cambridge = PostCovid + PostCovid × Cambridge (Models 4–5). Linear combinations are computed from reported point estimates only; no standard errors are implied. Joint significance tests for these linear combinations are available upon request. A dash denotes an effect that was not estimated.

6. Limitations and Directions for Future Research

There are several caveats to the results. These are primarily external validity issues, identification and time horizon issues, and they point towards where the results can be rolled out.

External validity. The study is focussed on the UK and Cambridge as a knowledge economy case. The findings may not apply to other economies, for example those that are developing, have large informal economies and/or are federated with highly decentralised fiscal powers. Trade-offs for recovery and factors that are contributing to inequality will probably be more complicated in these contexts.

Identification. Fixed-effects estimation controls for time-invariant city characteristics but does not control for time-varying city characteristics. Local fiscal interventions (small business grants, training schemes, etc.), the speed of digitalisation in certain sectors driven by the pandemic, as well as migration changes in connection with the pandemic and those resulting from Brexit, could have an impact on both outcomes and regressors. Furthermore, the coefficients for the time-invariant

indicators (Metropolis and Cambridge) are estimated using variation between cities rather than between individuals, and should be interpreted as conditional associations and not causal effects. There is also very limited time pre-pandemic for testing for parallel pre-trends, and the Cambridge estimates are based on only a single treated unit, making the standard errors less reliable; methods developed for one treated unit, like synthetic control, would be useful to test for parallel pre-trends.

City typology. Simple classification of "metropolitan" and "non-metropolitan" cities is based largely on population criteria. It does not take into account variations in industrial structure, public-sector employment, housing-market pressures and commuting across the metro category, which can significantly impact resilience, and the group-level difference may obscure this intra-group variation.

Time horizon. The 2019-2023 period refers to the early outbreak and recovery period, and does not include the impact of the outbreak over the longer-term. There might be a transitional phase as the structural impacts of the pandemic (skills, automation, inequality) only become evident over five, 10 or even 20 years. More significant relative progress of successful places and relative decline of lagging places will only become apparent in longer panels.

Econometric scope. Linear fixed-effects framework does not examine non-linearity amongst outcomes and important regressors or spatial dependence due to economic relations between neighboring areas, but diagnostic tests (Breusch–Pagan and Wooldridge and VIF) were performed. Not including inter-regional interaction can mask transmission mechanisms. Future research could therefore adopt spatial panel models (e.g. spatial lag or spatial error specifications) to address spatial dependence between neighbouring cities.

The constraints indicate three areas for further research: (i) cross-national panel data to control the influence of country characteristics and better capture the more general recovery patterns; (ii) quantitative analysis of mechanisms that explicitly include the role of upstream variables like investment in technology, industrial transformation and human-capital mobility as variables mediating the relationship between city type and recovery; and (iii) dynamic analysis of recovery using, for example, survival analysis or growth-curve models to characterise inflection points in recovery and the factors affecting them.

7. Conclusion

The results reveal spatial variation in the effects of COVID-19, and a "Matthew effect" is visible in the results. While Cambridge showed best performance in terms of income and welfare spending at net gain, the polarisation and income losses in large service-oriented metro cities were more pronounced, cities with strong human capital and good fiscal capacity and policy responsiveness tended to limit the losses but also saw smaller gains in welfare spending. The interaction effects provide evidence that the difference between advanced and lagging places increased in the recovery.

This resiliency comes at a social price. Agglomeration benefits economic recovery in the core areas by means of knowledge spillovers, economies of scale and improved infrastructure, but it does not benefit everyone equally. A shift into the high-technology and financial-services sectors, and the failure to grow in traditional and lower-paying service jobs, is contributing to urban inequality. Recovery benefits are therefore not distributed fairly and the disparity between economic growth and social equity is evident.

The results present a strong policy dilemma: how to transition from a limited efficiency-focused 'growth first' approach to a more holistic inter-regional development model that features city competitiveness. This necessitates a policy toolkit that is focused. The importance of support for innovation hubs and metropolitan ecosystems for national competitiveness is not changing, but should be accompanied by specific efforts at regional rebalancing, including (i) building human-capital capacity; (ii) closing the "digital divide" by investing in digital infrastructure to allow working from home and digital economic development; and (iii) creating new job hubs in less-developed regions through smart industrial policy. In a free market system, the system is likely to perpetuate geographical differences, with the "success breeding success" cycle potentially leading to social division and, over time, diminished overall vitality and resilience.

Further research is needed that uses a longer time-series and longitudinal design to better reflect the overall dynamics of the transition to the post-pandemic period and systematic cross-country comparison to distinguish country-specific elements from common post-pandemic dynamics. Ultimately, an inclusive recovery model will require the innovative dynamism of metropolitan areas coupled with institutional reform to take advantage of the new opportunities in the post-crisis environment

for all regions and social groups.

Funding

No

Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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