

State and Local CDBG-DR Implementation Capacity in Disaster Recovery: A Workload-Sensitive and Spatial Analysis

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Workload is the most consistent correlate of disaster recovery performance; observed resource effects depend on local data quality, while spatial diagnostics help target technical assistance.

INTRODUCTION: THE CHALLENGE

CDBG-DR converts federal appropriations into long-term housing and community recovery. Grantees differ in staffing systems, program portfolios, vulnerability, and implementation histories.

Capacity is defined as a workload-sensitive resource-workload balance specific to CDBG-DR, referring to CDBG-DR Fund Implementation Capacity – not as a ranking of government competence.

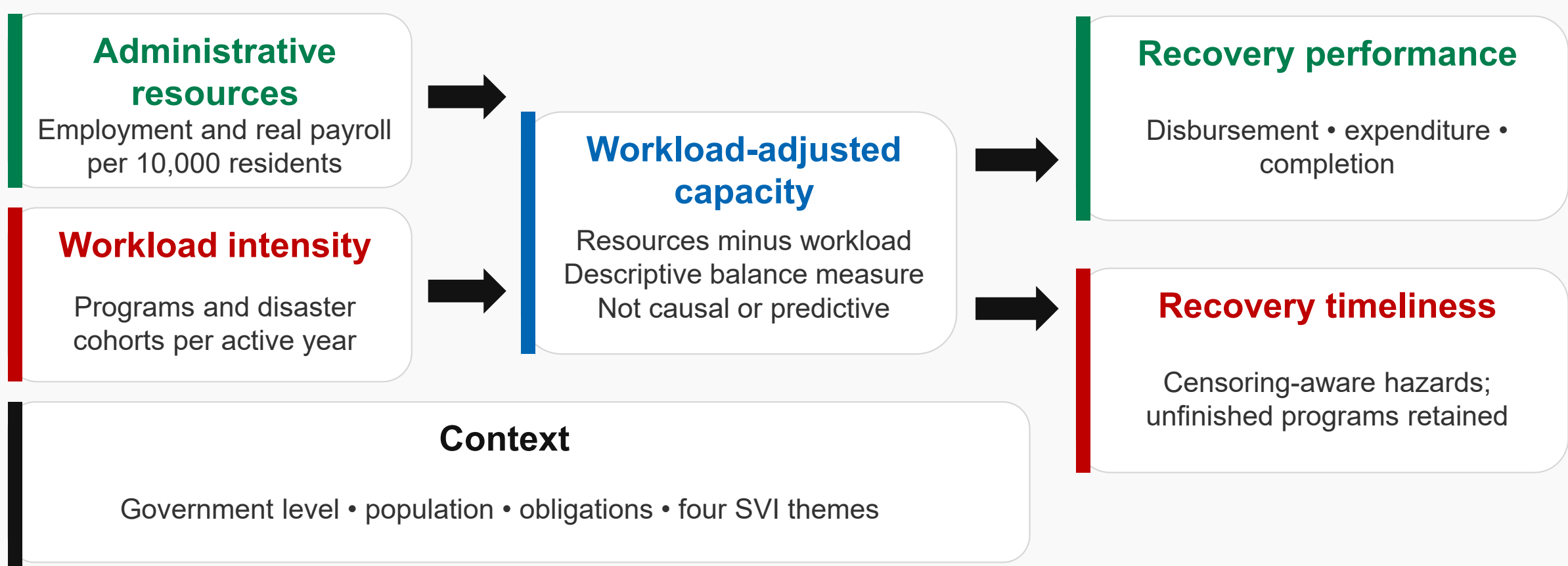
RESEARCH QUESTIONS

- How can implementation capacity be measured without conflating resources, workload, recovery need, and outcomes?
- How are resources and workload associated with performance and timeliness – and how sensitive are results to missing-data treatment?
- Where are capacity, implementation, and performance gaps spatially concentrated?

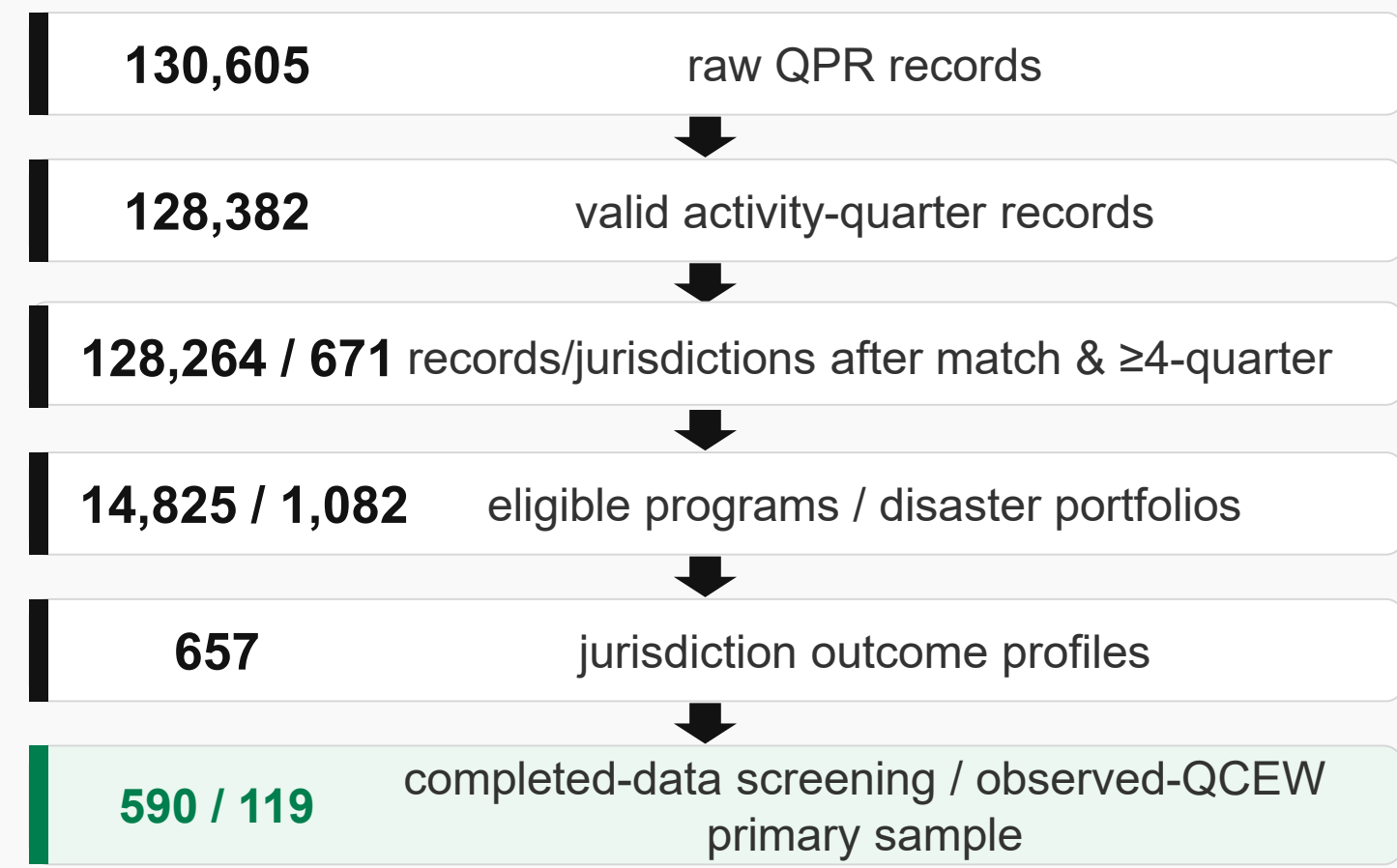
NATIONAL DATA FOUNDATION

130,605 raw DRGR/QPR records	128,382 valid activity-quarter records
14,825 eligible program profiles	590 / 119 final jurisdictions / directly observed primary sample

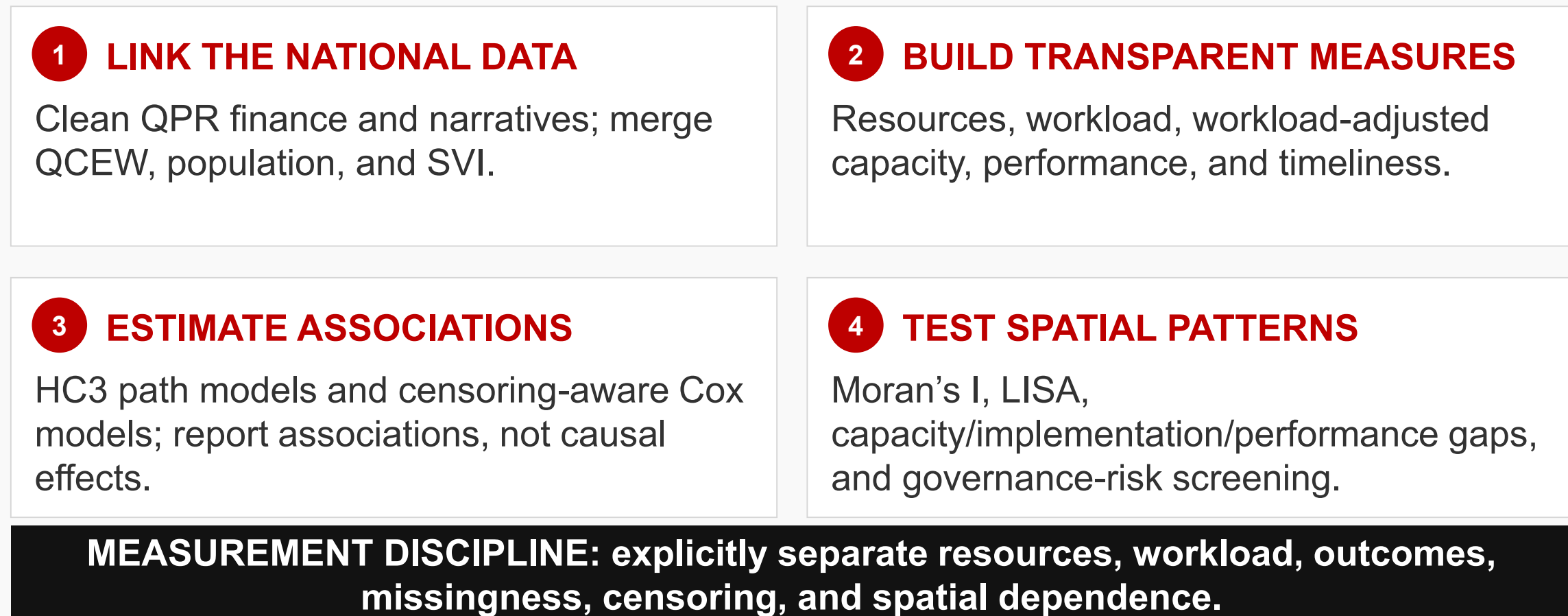
PROGRAM-SPECIFIC FRAMEWORK



SAMPLE CONSTRUCTION



ANALYTIC WORKFLOW

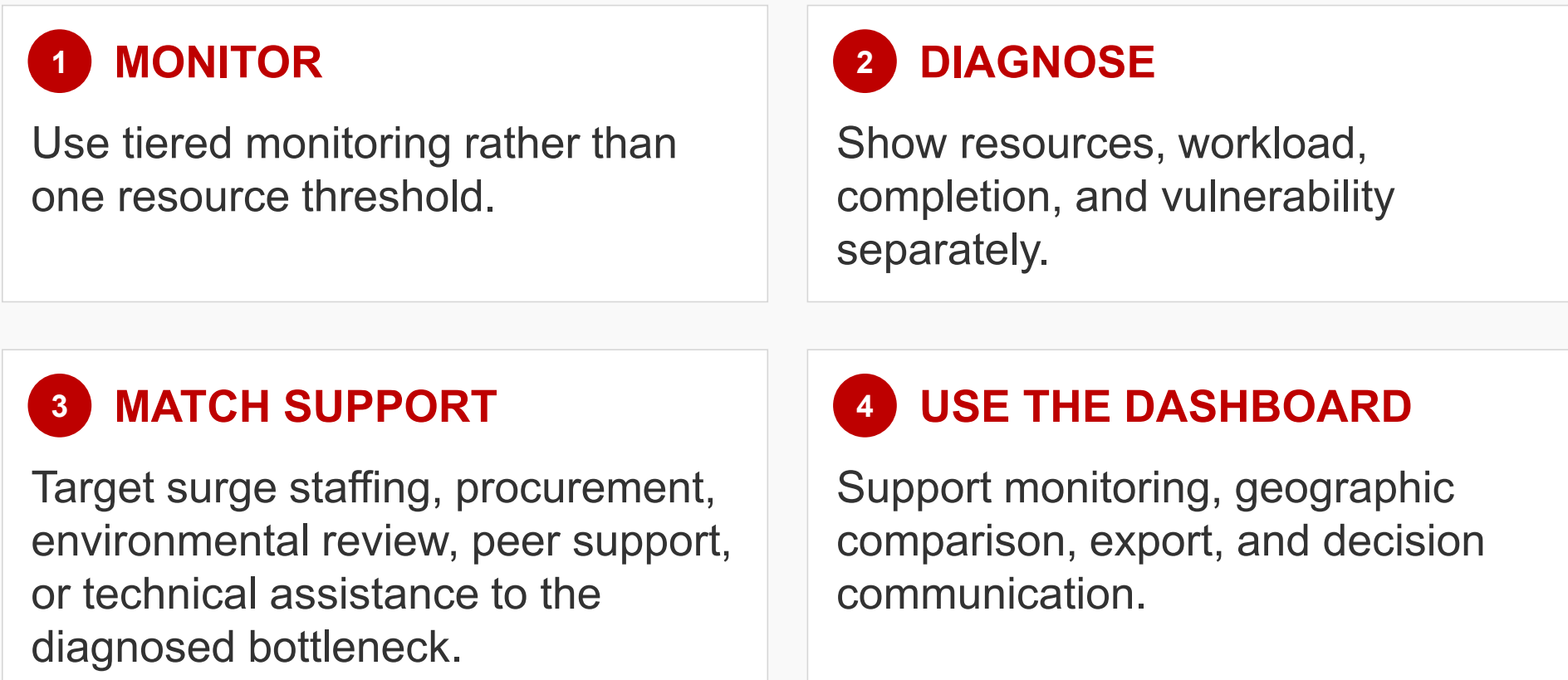


KEY FINDINGS: SHORT, SUPPORTED, AND SPATIALLY TESTED

+0.170 Resources → performance Observed local data; $p = .037$. The association disappears after population scaling.	-0.626 Workload → performance Observed-QCEW sample; $p < .001$. Largest and most stable result.	-0.289 Workload → timeliness Observed-QCEW sample; $p = .002$. Higher workload tracks slower progress.	0.633 Governance-risk Moran's I Permutation $p = .001$. Implementation conditions are geographically patterned.
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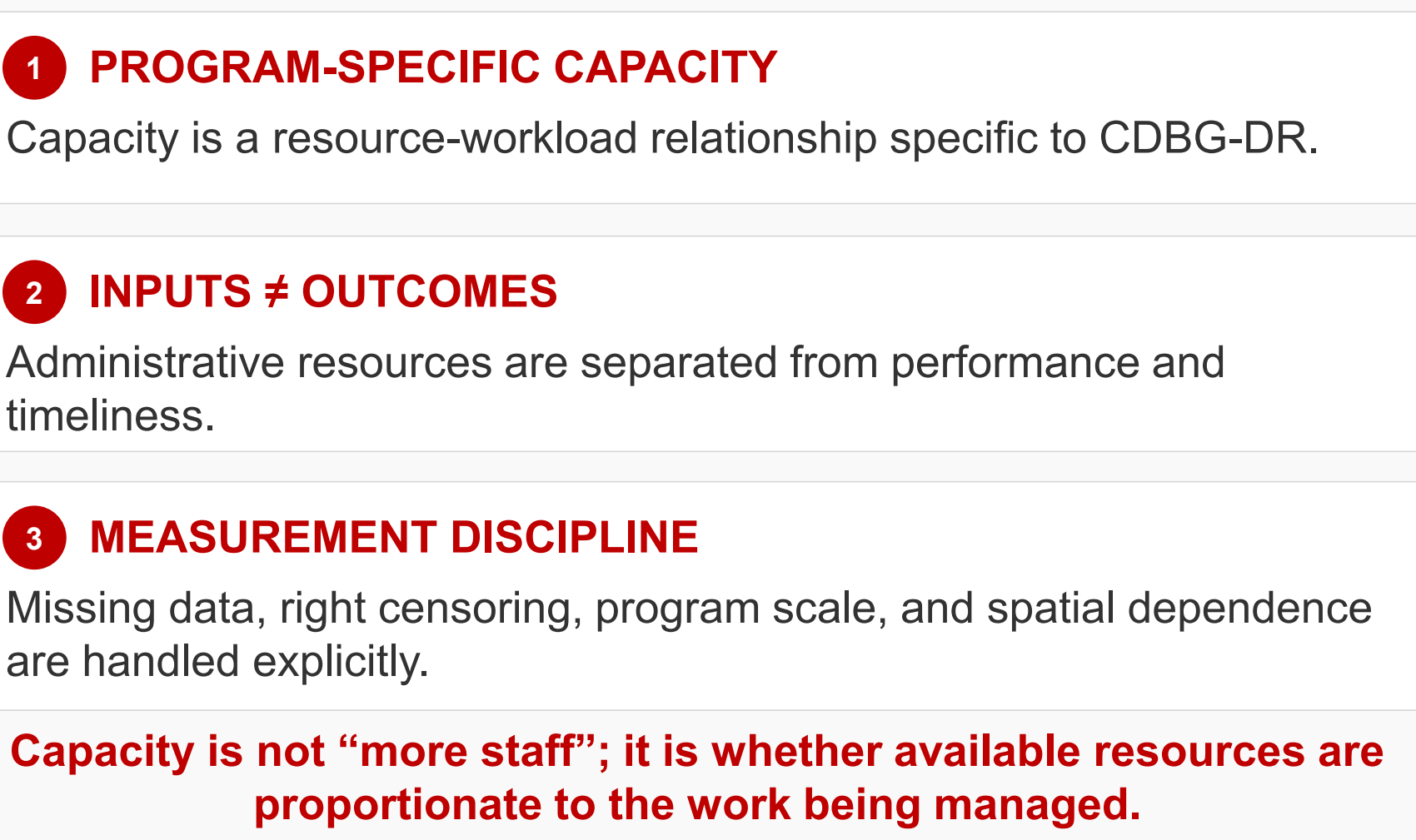
Predictor	Outcome / sample	Estimate	p	What the estimate means
Administrative resources	Performance – observed QCEW	$\beta = +0.170$	.037	Positive association only when local administrative data are directly observed.
Workload intensity	Performance – observed QCEW	$\beta = -0.626$	<.001	Greater portfolio demand is associated with substantially weaker financial execution.
Workload intensity	Timeliness – observed QCEW	$\beta = -0.289$	.002	Higher workload is associated with slower aggregate progress relative to follow-up time.
Administrative resources	Performance – completed data	$\beta = -0.007$	.841	The resource result is not reproduced after deterministic population scaling.
Log program obligation	95% completion – observed Cox	HR = 0.740	<.001	Larger programs have lower completion hazards, consistent with greater scale and complexity.
Additional completion result: greater household-composition/disability vulnerability is associated with lower completion hazards (SVI Theme 2, HR = 0.746, $p = .028$).				

PRACTICAL IMPLICATIONS



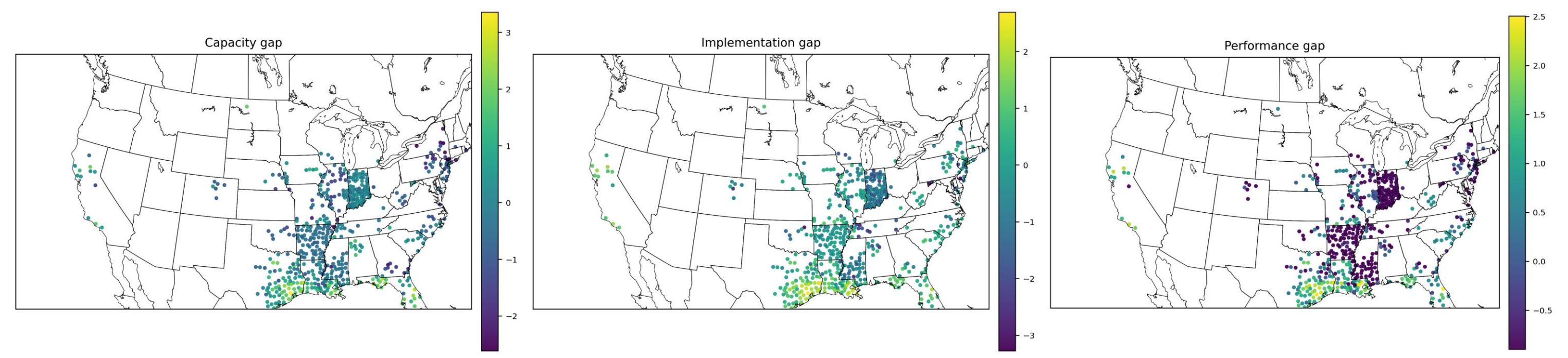
Decision principle: match support to the diagnosed bottleneck – not to a single score.

THEORETICAL CONTRIBUTIONS



Capacity is not “more staff”; it is whether available resources are proportionate to the work being managed.

SPATIAL GAPS, DEPENDENCE, AND TEXAS RELEVANCE



Measure	Moran's I	Permutation p
Capacity balance	0.628	.001
Recovery performance	0.584	.001
Recovery timeliness	0.422	.001
Governance risk	0.633	.001

WHAT STANDS OUT

94 of 558 counties exceed +1 standard deviation on the sample-relative governance-risk screen.
Texas accounts for 11 of the 20 highest county scores, including Harris, Hidalgo, Cameron, Jasper, and Jefferson.

Interpretation: spatial dependence identifies regional patterning, but the screen should prompt closer program review – not automatic ranking or funding decisions.

ACKNOWLEDGEMENTS & REFERENCES

We acknowledge the ASCE Texas Section and support by funding from the U.S. Department of Housing and Urban Development (Award H21749CA). The findings and conclusions are those of the authors and do not necessarily represent the official views of HUD.

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