One Nation, Under Aggregation: Twelve Federal Reserve Districts and the National Labor-Market Summary

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National labor-market statistics can be correctly centered while concealing substantial geographic variation. I ask how much observed variation is lost when state unemployment and vacancy conditions are summarized by twelve Federal Reserve district means and evaluated against an independently constructed national input. Using monthly data from 2001 through 2025, I separate variation averaged away within districts, variation preserved between them, and the national input's centering relative to the state-supported mean. Centering accounts for only 0.69 percent of state-to-national squared distance, while 53.99 percent is lost within districts and 45.32 percent remains between them. At the institutionally relevant scale of twelve regions, three illustrative procedures retain median labor-force-weighted shares of only 44–51 percent. Under an illustrative monetary-rule calibration and on the common 237-month support, district distances of at least 25 basis points expose 33.2 percent of the labor force on average; subtracting each district's strictly prior 60-month mean lowers exposure to 20.6 percent. The results do not prescribe regional interest rates or measure welfare losses; they show that evaluating an aggregate requires examining both its center and the regional distribution suppressed beneath it.

Keywords: regional aggregation; institutional regions; Federal Reserve districts; labor-market heterogeneity; national summary statistics
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1. Introduction

The Federal Reserve pursues a national employment objective with a national policy rate, but the labor-market conditions summarized by national statistics are geographically distributed. A national input can therefore look entirely reasonable in the aggregate while representing regional conditions unevenly. The difficulty is that closeness to the national number does not reveal how much local variation was pooled before that comparison was made. A correctly centered aggregate may still conceal a wide regional distribution.

This paper asks how much observed labor-market variation is lost when state-supported conditions are represented first by twelve Federal Reserve district means and then by one national input. I evaluate an independently constructed national unemployment–vacancy gap on this regional support; I do not claim that the national BLS series is literally produced by aggregating the districts. The answer is the paper's aggregation puzzle. The national input is almost exactly centered, yet district aggregation removes slightly more squared variation than it preserves, and the variation that survives between districts is often large enough to matter in familiar monetary-policy rule calibrations.

The paper's contribution is to show that evaluating an aggregate requires both its center and the geographic distribution suppressed beneath it. Regional science has long treated the definition of a region as part of the analysis (Isard 1956). The modifiable areal unit literature distinguishes the scale and zoning of spatial aggregation (Openshaw and Taylor 1979; Fotheringham and Wong 1991; Briant, Combes, and Lafourcade 2010), and regionalization methods make the map an object of statistical design (Openshaw 1977; Duque, Anselin, and Rey 2012; Bradley, Wikle, and Holan 2017). A national summary introduces a further margin: after a map replaces local observations with regional means, a scalar represents the remaining regional distribution. Applying a common accounting across these operations separates variation averaged away within regions, variation preserved between them, and the national input's centering relative to the state-supported mean.

Federal Reserve districts make that accounting economically consequential. They are durable, policy-facing supports through which regional information enters a national central-banking system (Goodfriend 1999; Board of Governors of the Federal Reserve System 2026). Research on FOMC preferences and voting shows that regional conditions can enter national deliberation even when national conditions remain central (Meade and Sheets 2005; Chappell, McGregor, and Vermilyea 2008; Bobrov, Kamdar, and Ulate 2025). Related work studies heterogeneous regional transmission and regional policy-rule prescriptions (Schunk 2005; Furceri, Mazzola, and Pizzuto 2019; Dominguez-Torres and Hierro 2019; Bennani 2016; Duran and Gajewski 2023; Coibion and Goldstein 2012; Malkin and Nechio 2012). I ask the prior measurement question: what distribution of regional conditions remains visible before one interprets transmission or compares prescriptions? The districts are evaluative supports, not asserted natural labor markets or candidate optimal policy regions.

I construct monthly state labor-market gaps from BLS unemployment and vacancy data for 299 months from January 2001 through December 2025. The gap uses the unemployment–vacancy efficiency benchmark in Michaillat and Saez (2024) and the state application in Pusateri (2026). County assignments allocate state gaps across split Federal Reserve districts, and labor-force weights aggregate the resulting cells to district means. An exact squared-loss identity locates variation within districts, between district means, and in the distance between the state-supported mean and the direct national input. I then vary the number of contiguous regions from one to 51 under three illustrative procedures, compare alternative zonings at twelve regions, and measure absolute district distance around the best common scalar. The procedures construct and weight connected partitions differently.

The exact decomposition reveals why centering alone is misleading. Within-district loss accounts for 53.99 percent of full-sample state-to-national squared distance, between-district loss for 45.32 percent, and centering for only 0.69 percent. Thus the observed national input lies near the state-supported center, but roughly half of the measured variation has already been pooled within districts and nearly half remains dispersed across district means. The within–between balance changes across historical windows, so the same well-centered national input represents different regional configurations over time.

The geographic evidence shows that both scale and zoning shape the loss. The one-region endpoint mechanically suppresses all cross-sectional dispersion. At twelve regions, the three procedures retain median labor-force-weighted shares from 44.1 to 51.2 percent, distinct from both the 45.32 percent fractional Federal Reserve accounting and the 47.96 percent whole-state analogue. Each region-count distribution is generated separately, and the three procedures are illustrative rather than exhaustive. The retained share rises more per added region before twelve than after twelve under all six procedure-by-weighting comparisons, while the fixed-12 sensitivity shows that zoning also changes the within–between allocation.

The surviving variation is economically legible under the simple-rule benchmark in Taylor (1993). Mean absolute district-to-common-input distance is 0.418 gap percentage points. Under the illustrative coefficient $\phi_x = 0.50$, a 0.50-point residual maps to 25 basis points in the rule term. At twelve regions, median within-region RMS loss is 29–31 rule-input basis points across the three procedures. The procedure-specific medians do not remain below 25 basis points until the scale reaches between 18 and 21 regions. This is a crossing under one calibration, not an optimal count or a proposed institutional design. Among the observed Federal Reserve districts, residuals at or above 25 basis points expose 32.3 percent of the labor force on average and occur in 94.0 percent of months. Removing each district's strictly prior 60-month location lowers matched-support exposure from 33.2 to 20.6 percent. These are descriptive rule-equivalent distances, not estimates of district-specific policy rates or welfare losses.

The paper therefore shifts the evaluative question. The relevant test is not only whether a national number sits near the center of regional conditions, but how much geographic variation is no longer visible when that center is assessed. The sections that follow construct the representation ladder, measure its three margins, separate scale from zoning, establish the magnitude and incidence of the remainder, and bound the interpretation with direct measurement checks.

2. The Analytical Ladder: Data and Institutional Support

The empirical problem is an evaluative representation ladder with two analytical stages. A regional map replaces state-supported observations with district means; a scalar then represents the district distribution. The national input is constructed directly from national BLS series rather than by either stage. I measure the loss associated with evaluating that independent national object on the same unemployment–vacancy gap axis. The exercise is an accounting of representation under a stated loss function.

Throughout the paper, information means observed cross-sectional variation under the stated squared- and absolute-distance loss functions. It does not mean entropy, predictive content, or the complete information set relevant for monetary policy. This definition keeps the empirical question narrow: how much of the measured regional distribution remains visible after a map and a scalar represent it?

2.1. State labor-market gaps

The state input combines monthly unemployment from BLS Local Area Unemployment Statistics, published State JOLTS job-openings rates, and the unemployment–vacancy efficiency benchmark in Michaillat and Saez (2024). I use the state-level construction developed in Pusateri (2026). For state i in month t, define

$$x_{it} = u^*_{it} - u_{it}, \qquad u^*_{it} = 100\sqrt{\left(\frac{u_{it}}{100}\right)\left(\frac{v_{i,t-1}}{100}\right)}.$$

Here u_{it} is the unemployment rate and $v_{i,t-1}$ is the State JOLTS job-openings rate labeled for the prior month. The gap x_{it} is measured in percentage points; a larger value indicates tighter conditions because unemployment is farther below the benchmark implied by unemployment and vacancies.

The current-vintage sample contains 299 eligible months from January 2001 through December 2025. I pair LAUS month t with State JOLTS label $t-1$ under a rule fixed across the sample. October 2025 remains on the analysis calendar but is unusable because all 51 state/DC LAUS unemployment and labor-force inputs are missing; November and December remain usable. The pairing aligns reference periods rather than release dates and does not reconstruct a real-time information set.[1]

2.2. Fractional district aggregation

Federal Reserve districts are inherited banking-administrative regions, not a partition designed around modern labor markets.[2] Reserve Banks remain regional components of a national central-banking system and collect, interpret, and communicate information about their districts (Goodfriend 1999; Board of Governors of the Federal Reserve System 2026). That continuing role makes the inherited map relevant to a national labor-market summary. The baseline does not choose boundaries to maximize within-region homogeneity. Optimized regionalization answers a different question: which partition best satisfies a stated criterion (Duque, Anselin, and Rey 2012; Bradley, Wikle, and Holan 2017).

Let a_{id} be the share of state i assigned to district d, and let L_{it} denote the state labor force. A state wholly inside one district has one nonzero share. Fourteen state/DC units cross district boundaries and enter as fractional state–district cells. The baseline shares use 2019 county population, while the monthly exposure weights use state labor force:

$$L_{dt} = \sum_i a_{id} L_{it}, \qquad x_{dt} = \frac{\sum_i a_{id} L_{it} x_{it}}{L_{dt}}, \qquad w_{dt} = \frac{L_{dt}}{\sum_{d'} L_{d't}}.$$

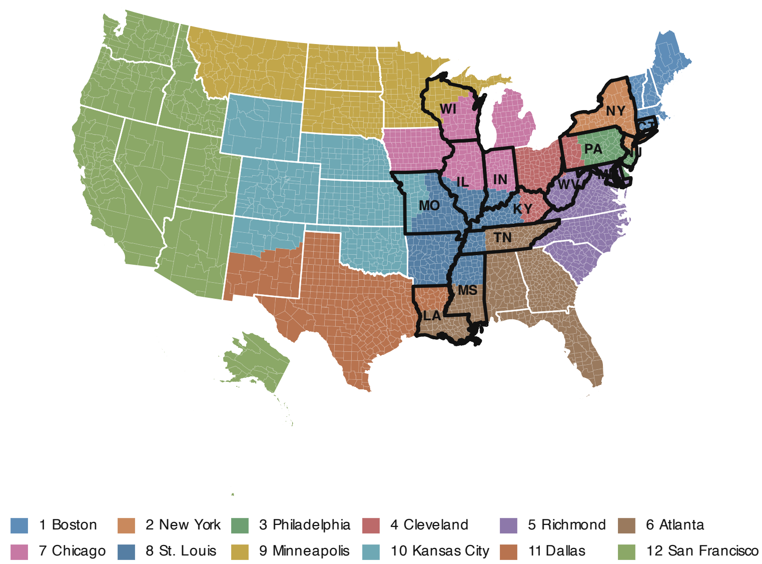
[1] LAUS refers to the CPS week containing the 12th, whereas State JOLTS measures the last business day of its label month. On the fixed calendar, the last business day of $t-1$ is closer to the LAUS reference week in 280 of 300 months, ties in 16, and is farther away in four short-February cases. The calendar contains 300 months; October 2025 remains in this reference-date comparison but is omitted from the 299-month estimation panel because its state/DC LAUS inputs are missing. Appendix A records sources, units, coverage, and the fractional district allocation.

[2] The map was neither drawn on a blank slate nor accepted quietly. The Federal Reserve Act instructed the committee to create between eight and twelve districts with "due regard to the convenience and customary course of business." In 1914, the committee heard claims from more than 200 cities—37 sought a Reserve Bank—and sent a preference ballot to 7,471 national banks. At the Kansas City hearing, Secretary of Agriculture David Houston captured the local boosterism: "Each place we go is the center." The committee emphasized banking connections and capital, geography, transportation and communication, population, and growth prospects (Reserve Bank Organization Committee 1914; Hammes 2001). Later work examines city selection and shows that bank preferences and correspondent relationships predicted district boundaries (McAvoy 2006; Jaremski and Wheelock 2017).

The county crosswalk determines how state observations are allocated; it does not supply county vacancy gaps. State gaps remain the primitive measurement at every stage.

Figure 1 makes the institutional support explicit before the two stages of representation loss are defined.

FIGURE 1. Federal Reserve District Support



Note: County polygons inherit the district assignment used to allocate state-level labor-market gaps. Outlines identify state/DC units split across districts. The map defines the aggregation support; it is not county-level vacancy-gap evidence. Sources are the Federal Reserve county–district crosswalk and 2019 Census cartographic county boundaries.

For the exact accounting, index each positive state–district cell by $q = (i, d)$. Let $x_{qt} = x_{it}$ and $\alpha_{qt} = a_{id} L_{it} / \sum_j L_{jt}$. Then $\sum_q \alpha_{qt} = 1$, $\sum_{q \in d} \alpha_{qt} = w_{dt}$, and the district mean is the weighted average of its cells. Define the state-supported mean $\bar{x}_t = \sum_q \alpha_{qt} x_{qt} = \sum_d w_{dt} x_{dt}$.

2.3. Exact representation-loss accounting

The directly constructed national input is

$$x_t^0 = u_t^* - u_t, \qquad u_t^* = 100\sqrt{\left(\frac{u_t}{100}\right)\left(\frac{j_{t-1}}{100}\right)},$$

where u_t and j_{t-1} are national BLS unemployment and prior-label job-openings rates. These national products are constructed independently of the state-to-district aggregation. Because the benchmark is nonlinear and the underlying official-statistics systems differ, x_t^0 need not equal $\bar{x}_t$; the centering term measures that discrepancy rather than a second step in the production of the national series.

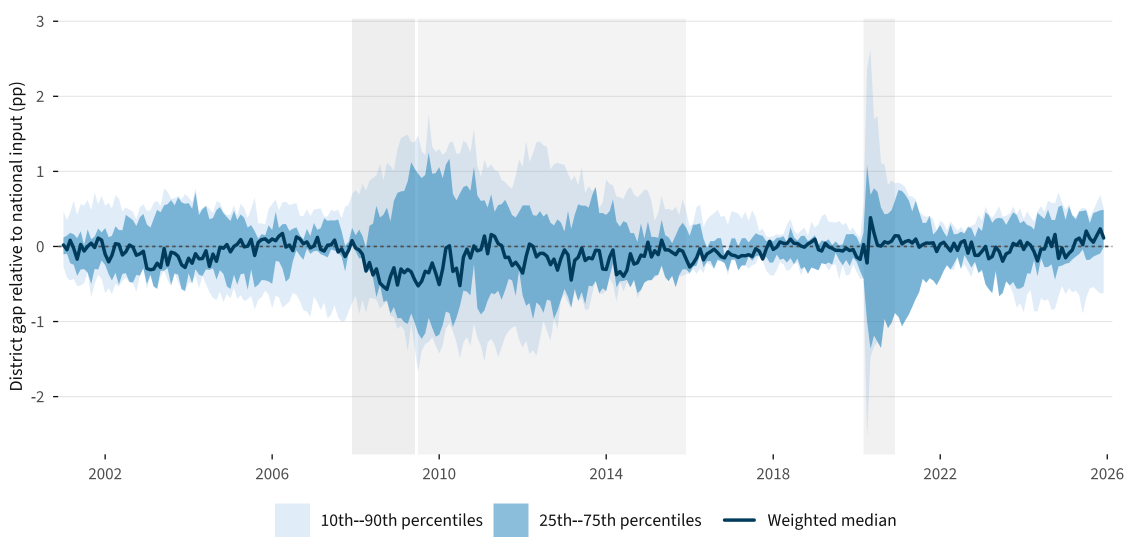
[Table 1](#) distinguishes the primitive observations, regional means, and national objects used in the exact accounting.

TABLE 1. Representation Objects and Exact Squared-Distance Accounting

Object	Symbol	Center or benchmark	Empirical job
State-supported cell	$x_{qt} = x_{it}$	None	Primitive signal, with county geography used only for fractional allocation
District mean	x_{dt}	State-supported cells in district d	Signal preserved after regional aggregation
State-supported mean	$\bar{x}_t$	Labor-force-weighted state support	Squared-distance-minimizing mean implied by the state-supported panel
Direct national input	x_t^0	National BLS unemployment and JOLTS	Independently constructed scalar evaluated on the regional support
Exact squared-distance accounting	Equation (1)	District means, $\bar{x}_t$, and x_t^0	Additive within, between, and centering squared distance

Note: Squared-distance components are measured in squared gap percentage points before window averaging; reported RMS levels take square roots afterward. The direct national input is constructed independently of the state-supported panel.

FIGURE 2. Federal Reserve District Gaps Relative to the National Input



Note: Bands report the labor-force-weighted 10th–90th and 25th–75th percentiles of the twelve district gaps $x_{dt} - x_t^0$. A weighted quantile is the smallest ordered district value whose cumulative labor-force weight reaches the stated probability. The solid line is the labor-force-weighted district median, and the dashed zero line is the directly constructed national input. Episode shading marks the GFC, ZLB, and COVID windows used for descriptive comparisons; it does not identify causal effects. The figure uses the raw current-vintage state-supported estimand and the fractional Federal Reserve district allocation.

Before decomposing that distance, Figure 2 shows the distribution that the national scalar represents. Each month, the bands are labor-force-weighted inverse-empirical-CDF quantiles of $x_{dt} - x_t^0$; the solid line is the weighted median. The median remains near zero in many months even when the middle half and wider district distribution span economically meaningful distances. The national input can therefore be close to the center without making the district distribution narrow. The distribution widens most visibly during the GFC/ZLB and COVID periods, but it does not collapse to zero outside those episodes.

The figure reveals the surviving distribution, but not how much variation the district map removed before the district means were formed. The exact accounting supplies that missing margin. Squared distance from state-supported inputs to the national input has the monthly decomposition

$$\sum_q \alpha_{qt}(x_{qt} - x_t^0)^2 = \underbrace{\sum_d \sum_{q \in d} \alpha_{qt}(x_{qt} - x_{dt})^2}_{\text{within-district loss}} + \underbrace{\sum_d w_{dt}(x_{dt} - \bar{x}_t)^2}_{\text{between-district loss}} + \underbrace{(\bar{x}_t - x_t^0)^2}_{\text{centering loss}} . \qquad (1)$$

Within-district loss is the state-supported variation averaged away by the district map. Between-district loss is the variation that survives in district means before one common scalar represents them. Centering loss is the squared distance between the state-supported mean and the observed national input. Window statistics average the squared components equally across months before taking roots or shares, so Equation (1) remains exact. Months receive equal weight because the estimand is representation loss in the average eligible month; labor-force weights operate within months rather than across them.

3. How Much Information Is Lost?

Figure 2 shows that the national input can remain near the center even when the district distribution is wide. Table 2 locates the source of that dispersion. Across the full sample, district aggregation removes 54.0 percent of state-to-national squared distance, while 45.3 percent survives between districts; the national input's centering accounts for only 0.7 percent. The central issue is therefore geographic representation, not whether the national scalar is centered correctly.

TABLE 2. Two Stages of Representation Loss

		RMS gap percentage points			Share of total squared distance		
Window	Months	Within	Between	Centering	Within	Between	Centering
Full available	299	0.616	0.564	0.070	54.0%	45.3%	0.7%
Ordinary pre-2020	131	0.440	0.363	0.056	59.0%	40.1%	0.9%
GFC/ZLB	97	0.819	0.748	0.082	54.2%	45.3%	0.5%
COVID shock	10	1.229	1.098	0.115	55.3%	44.2%	0.5%
Reopening / inflation	59	0.364	0.442	0.063	39.9%	58.9%	1.2%

Note: The table reports the exact squared-distance accounting for current-vintage state-supported UV-gap inputs. The sample contains complete monthly state/DC support from January 2001 through December 2025; split states enter as fractional state-district cells weighted by labor-force exposure. Within loss is squared cell distance from district means, between loss is squared district-mean distance from the state-weighted mean, and centering is squared distance from that mean to the directly constructed national input. Window levels are square roots of equal-month mean squared components; shares divide each mean squared component by total state-to-national squared distance. Squared-distance shares are distinct from the absolute-distance materiality shares reported later and are not welfare shares.

3.1. The two-stage accounting

The RMS levels tell the same story in gap-percentage-point units. Across all 299 months, within-district loss has an RMS magnitude of 0.616, compared with 0.564 for between-district loss and 0.070 for centering. A differently located national input could reduce the small centering component, but it could not recover the variation removed within districts or the dispersion that remains between them.

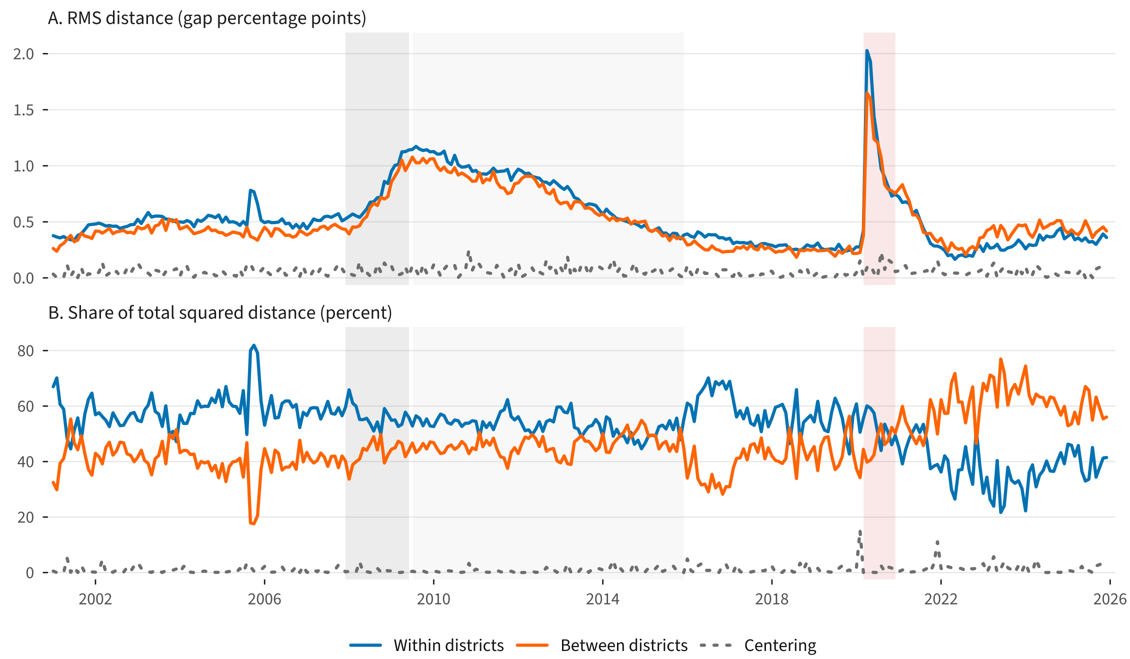
The within–between balance changes over time. Within-district loss accounts for 59.0 percent of total squared distance in ordinary pre-2020 months and 55.3 percent during the COVID shock. During reopening and inflation, the balance reverses: between-district loss accounts for 58.9 percent and within-district loss for 39.9 percent. These are descriptive episode comparisons. They show that the information removed by regional averaging and the information left for a common scalar are separate time-varying margins.

3.2. When the losses change

Figure 3 shows the monthly RMS levels and component shares. Both within- and between-district losses rise during the GFC/ZLB period and the COVID shock. Their paths are related but not interchangeable: months with similar total state dispersion can place different shares of that distance inside districts and between them.

The exact accounting establishes the two margins for the institutional (K=12) support. It does not show whether twelve regions generally retain this amount of state variation or whether the particular Federal Reserve zoning drives the result. The next section separates those two geographic questions.

FIGURE 3. Representation Loss over Time



Note: Panel A reports monthly RMS gap-percentage-point components from Equation (1). Panel B reports their shares of total monthly squared distance. Episode shading is descriptive and does not identify causal effects. The figure uses current-vintage BLS state unemployment and vacancy inputs from January 2001 through December 2025 and the fractional Federal Reserve district allocation.

4. How Scale and Zoning Shape Geographic Loss

The institutional accounting leaves a geographic question open. Twelve Federal Reserve districts preserve 45.32 percent of state-to-national squared distance between district means, but that share reflects both the number of regional summaries and the states assigned to them. Geographic scale fixes the number of regions; zoning determines which states are averaged together at a given count. I separate these margins by varying scale from one to 51 regions and then holding the count at twelve while changing the zoning.

The reference maps partition 51 whole state/DC units. To place Federal Reserve districts on the same support, I assign each state to the district receiving its largest baseline allocator share. This whole-state Federal Reserve analogue is comparable to the reference maps, but it is not the primary fractional district measurement.

Three neighboring twelve-region quantities use different supports and denominators. The 45.32 percent institutional share comes from the fractional Federal Reserve allocation and divides by total state-to-national squared distance. The whole-state Federal Reserve analogue instead retains 47.96 percent of state dispersion around the state-supported mean.

The synthetic $K = 12$ distributions below have procedure-specific labor-force-weighted medians from 44.1 to 51.2 percent. These are related accounting objects, not alternative estimates of one parameter.

4.1. Geographic scale and the compression curve

The scale exercise uses the same 299-month state/DC panel as the main accounting. Under labor-force weighting, the retained share divides between-region squared distance by fixed state dispersion around the monthly state-supported mean. The equal-region companion changes the effective state weights and divides between-region squared distance by that map's within-plus-between total. The two panels thus report distinct estimands.

Figure 4 compares three illustrative procedures for constructing connected partitions. The procedures differ in how they construct and weight those partitions. These are informative contrasts, not an exhaustive set of possible map-generating procedures.[3]

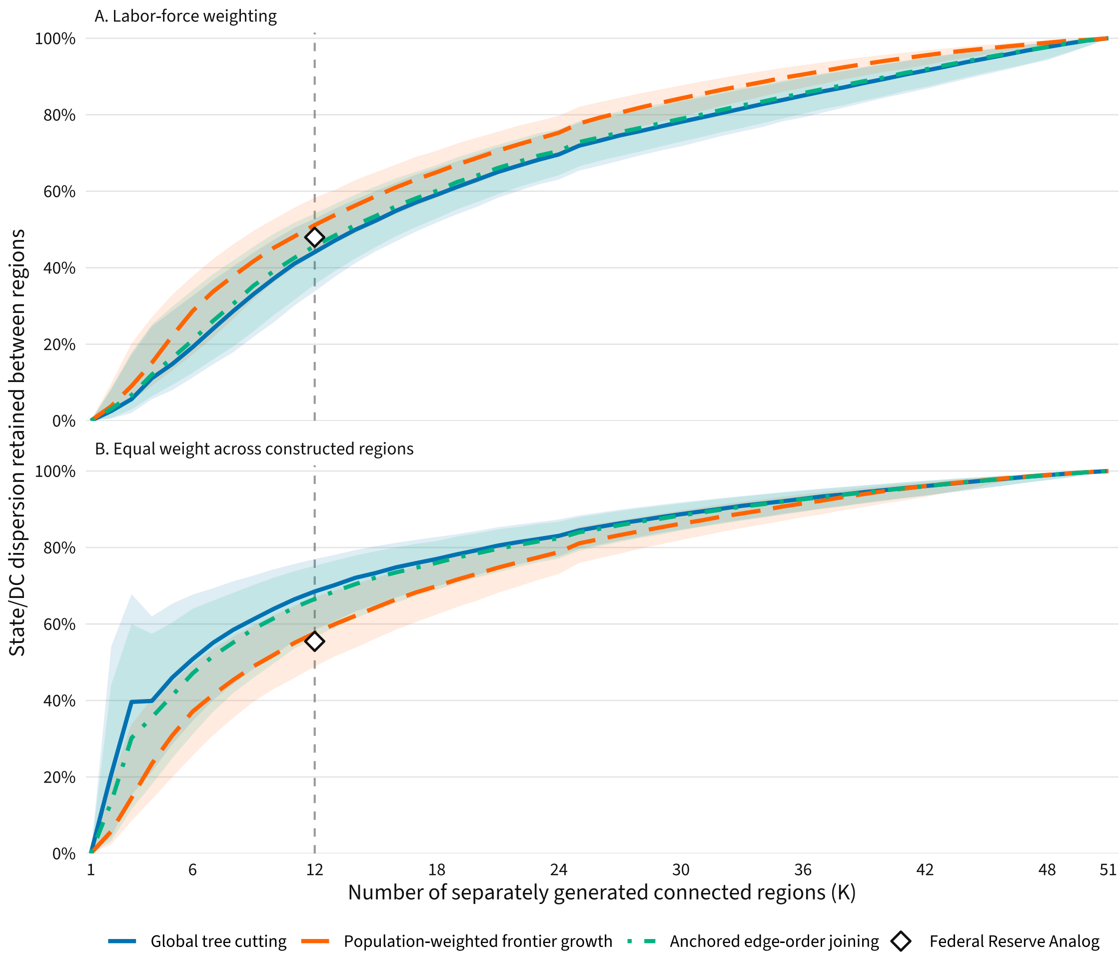
The one-region endpoint is mechanical: one aggregate cannot preserve cross-sectional dispersion. The live benchmark is whether twelve regions preserve enough of the state distribution to make the remaining loss modest. Across the separately generated $K = 12$ distributions, the three procedures retain median labor-force-weighted shares from 44.1 to 51.2 percent. The bands around those medians show zoning dispersion within each procedure, while the shifts across procedures show sensitivity to the construction. The K distributions are generated separately, so higher region counts are not recursive subdivisions of the twelve-region maps.

All six procedure-by-weighting median curves rise more per added region from $K = 3$ to $K = 12$ than from $K = 12$ to $K = 50$. This comparison supports a common steep-then-flattening pattern within the three illustrations without implying global concavity or invariance to map design. The $K = 51$ endpoint then shows what no geographic aggregation means; it does not identify an optimal scale.

The whole-state Federal Reserve analogue lies inside all three labor-force-weighted $K = 12$ distributions. Under equal-region weighting, its location approaches the lower tail under two procedures. The contrast reinforces the distinction between an institutional benchmark and a probability statement over possible map-generating procedures.

[3] Appendix Tables C2 to C4 report the construction contrasts, conditional support, benchmark distributions, and scale comparisons.

FIGURE 4. Geographic Scale and the Share of State Dispersion Retained



Note: Lines are procedure-specific medians and ribbons are the corresponding 10th–90th percentile ranges. The white diamond is the whole-state Federal Reserve analogue at $K = 12$, which is distinct from both the synthetic distributions and the fractional institutional accounting. The one-region and 51-region values are mechanical full-compression and no-aggregation endpoints. The procedures represent distinct constructions of connected partitions, and they are illustrative rather than exhaustive. The analysis assigns no probability weighting across procedures. Each K is a separately generated distribution, not a nested refinement of the $K = 12$ maps. Each ribbon is the 10th–90th percentile range under one procedure's induced distribution, not a confidence interval or a pooled cross-procedure distribution. The sample contains 50 states plus the District of Columbia over 299 months.

4.2. Fixed-12 zoning and institutional support

Unlike the dense-K exercise, which imposes only an upper share cap, fixed-12 zoning isolates more similarly balanced contiguous regions. It requires every region's 2019 labor-force share to fall within the whole-state Federal Reserve analogue's regional share range, expanded by one percentage point at each end. Under labor-force weights, every sampled map lies on the same total-variance frontier; equal-region weighting changes the effective state weights and allows total variation to differ. The Federal Reserve analogue's location in this conditional design confirms that grouping matters even when the region count stays fixed. Under labor-force weights, its within-region loss lies at the 79.29th percentile of the sampled maps, with between-region retention at the complementary 20.71st percentile.[4] Scale and zoning thus answer different questions. The next section asks whether the variation that survives both margins is large enough to matter under the stated rule-equivalent calibration.

5. Does the Remaining Variation Matter?

The preceding sections use squared distance to determine where geographic variation is lost. Materiality is a different question: how far the surviving observations lie from a common location. Absolute loss supplies that companion measure. Let m_t be the labor-force-weighted district median and define

$$B_t = \min_c \sum_d w_{dt} |x_{dt} - c| = \sum_d w_{dt} |x_{dt} - m_t|.$$

State-to-district compression uses cell residuals $r^1_{qt} = x_{qt} - x_{dt}$, weighted by α_{qt}. District-to-common-input distance uses district residuals $r^2_{dt} = x_{dt} - m_t$, weighted by w_{dt}. The full-sample mean absolute district distance is 0.418 gap percentage points. These absolute distances are not additive with the squared components in Equation (1); they measure the absolute distance that the relevant common location cannot remove.

I translate those distances into illustrative contributions to a stated Taylor-rule term, not realized interest rates. Simple rules are transparent benchmarks that policymakers may consult without mechanically following any one prescription, and their small set of inputs omits other considerations (Taylor 1993; Board of Governors of the Federal Reserve System 2025). If the coefficient on the labor-market gap is ϕ_x, a residual of r gap percentage points contributes $100\phi_x r$ basis points. The prespecified baseline $\phi_x = 0.50$ maps absolute residuals of 0.50 and 1.00 gap percentage points into 25 and 50 basis points. The 25-basis-point cutoff is a familiar policy increment, not an estimate of how the FOMC would respond; all results remain in gap-percentage-point units.[5]

Applying $\phi_x = 0.50$ to the within-region RMS levels, the $K = 12$ medians equal 29–31 rule-input basis points across the three procedures. This calculation is separate from the absolute district-distance analysis. The first sustained crossing below 25 basis points occurs between 18 and 21 regions, depending on the procedure. Each K is generated

[4] Figure C1 and its detailed frontier discussion appear in Appendix C.

[5] Appendix Table C1 reports the prespecified coefficient grid $\phi_x \in \{0.25, 0.50, 1.00\}$ and its implied gap thresholds.

separately, so the range is not a subdivision path. It also does not identify an optimal count or institutional recommendation.

For each threshold, I report exposed labor-force shares, affected counts, the share of months with a crossing, and consecutive-month spell lengths. A demeaning companion subtracts each district's mean over 60 strictly prior consecutive eligible months and then recomputes the contemporaneous weighted median on the common 237-month support. It isolates variation beyond recent district location without changing the raw district-to-common-input estimand. Table 3 measures the variation removed when states are summarized by districts, while Table 4 measures the mismatch that remains when one common input represents those districts. Table 5 then asks how much of the latter survives after removing each district's recent location.

TABLE 3. State-to-District Rule-Equivalent Exposure

		Mean exposed labor-force share	
Window	Months	25 bp	50 bp
Full available	299	27.0%	8.6%
GFC/ZLB	97	41.3%	16.6%
COVID shock	10	52.4%	26.1%
Reopening / inflation	59	13.4%	2.2%

Note: Exposure is the monthly labor-force share of fractional state–district cells whose absolute residual from the district mean reaches the stated threshold, averaged equally across months. Under the display calibration $\phi_x = 0.50$, 25 and 50 basis points correspond to absolute residuals of 0.50 and 1.00 gap percentage points. These are illustrative rule-equivalent contributions, not realized policy rates, policy errors, district recommendations, or welfare effects. Window labels are descriptive, not causal.

TABLE 4. District-to-Common-Input Exposure and Persistence

		Mean exposed labor-force share		Persistence at 25 bp		
Window	Months	25 bp	50 bp	Districts	Any month	Maximum run
Full available	299	32.3%	8.5%	4.0	94.0%	117
GFC/ZLB	97	49.1%	20.1%	6.2	100.0%	97
COVID shock	10	62.1%	41.6%	7.4	100.0%	10
Reopening / inflation	59	27.5%	2.0%	2.7	98.3%	20

Note: Exposure is the monthly labor-force share of districts whose absolute residual from the contemporaneous labor-force-weighted district median reaches the stated threshold, averaged equally across months. Districts, any month, and maximum run are reported at 25 basis points; maximum run is the longest district-specific sequence of consecutive monthly crossings in the window. Under the display calibration $\phi_x = 0.50$, 25 and 50 basis points correspond to absolute residuals of 0.50 and 1.00 gap percentage points. These are illustrative rule-equivalent contributions, not realized policy rates, policy errors, district recommendations, or welfare effects. Window labels are descriptive, not causal.

TABLE 5. Prior-Window-Demeaned District Exposure and Persistence

		Raw matched exposure		Demeaned exposure		Demeaned at 25 bp	
Window	Months	25 bp	50 bp	25 bp	50 bp	Districts	Maximum run
Full available	237	33.2%	10.5%	20.6%	3.6%	2.5	35
GFC/ZLB	97	49.1%	20.1%	34.3%	5.1%	4.2	28
COVID shock	10	62.1%	41.6%	55.5%	28.6%	6.1	9
Reopening / inflation	57	27.7%	2.1%	5.8%	0.3%	0.6	14

Note: The raw and demeaned columns use identical matched support. The demeaned companion subtracts each district's mean over 60 strictly prior consecutive eligible calendar months and then recenters the resulting district values on their contemporaneous labor-force-weighted median. Districts and maximum run are reported for the demeaned companion at 25 basis points; maximum run is the longest district-specific sequence of consecutive monthly crossings in the window. Under the display calibration $\phi_x = 0.50$, 25 and 50 basis points correspond to absolute residuals of 0.50 and 1.00 gap percentage points. These are illustrative rule-equivalent contributions, not realized policy rates, policy errors, district recommendations, or welfare effects. The complete appendix grid separately reports median positive spell length. Window labels are descriptive, not causal.

5.1. Incidence across districts and episodes

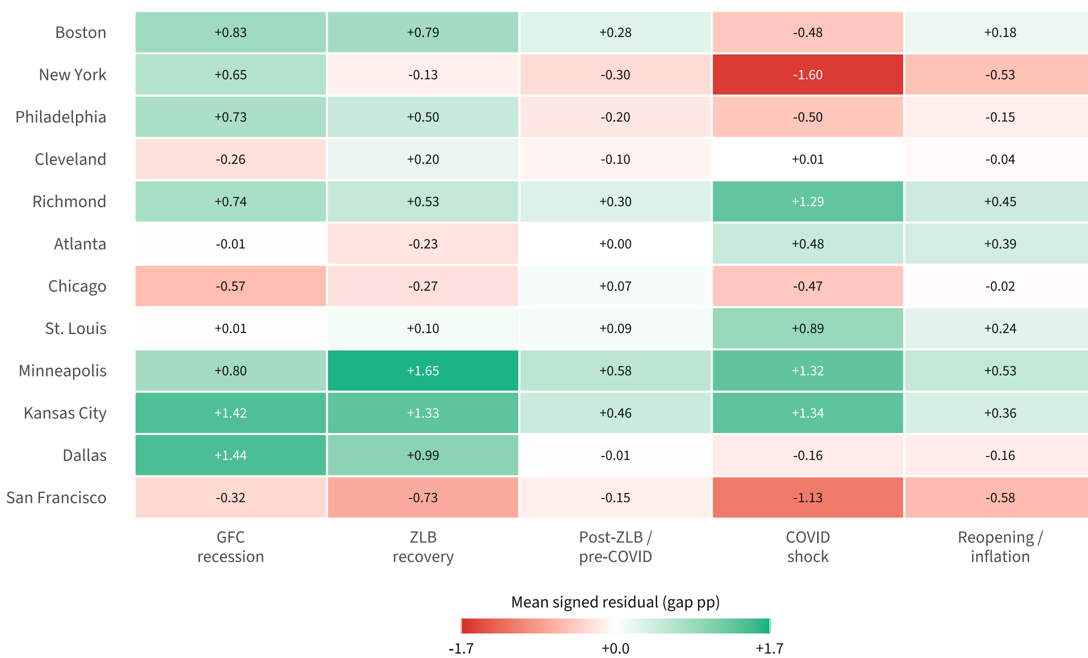
For state-to-district compression, cell residuals of at least 0.50 gap percentage points expose an average 27.0 percent of the national labor force over the full sample; the 1.00-point threshold exposes 8.6 percent. For district-to-common-input distance, the corresponding shares are 32.3 and 8.5 percent. A 25-basis-point district crossing occurs in 94.0 percent of months, affects 4.0 districts in the average month, and has a 117-month maximum district-specific run, driven by Minneapolis. That maximum should not be mistaken for a typical spell: the median positive district spell lasts 1 month. The 50-basis-point threshold is less common but still exposes 8.5 percent of the labor force on average. Missing calendar months break a spell rather than being bridged.

Table 5 shows that persistent district location explains part, but not all, of the remaining mismatch. On matched support, prior-window demeaning lowers 25-basis-point exposure from 33.2 to 20.6 percent and 50-basis-point exposure from 10.5 to 3.6 percent. The attenuation is uneven across episodes: demeaned exposure remains 55.5 and 28.6 percent at the two thresholds during the COVID shock, but falls to 5.8 and 0.3 percent during reopening and inflation. The common-input mismatch therefore contains both persistent district differences and substantial departures from recent district location in the periods of greatest dispersion.

Historical windows locate, rather than identify, the highest incidence. During the GFC/ZLB period, district exposure averages 49.1 percent at 25 basis points and 20.1 percent at 50 basis points. During the COVID shock the shares are 62.1 and 41.6 percent. Reopening and inflation produce a different pattern: 25-basis-point district exposure remains 27.5 percent, while 50-basis-point exposure falls to 2.0 percent. The threshold results therefore add frequency, exposure, and duration to the mean-distance evidence rather than selecting a single episode or tail statistic.

The districts contributing to those exposure shares change across episodes. Figure 5 reports each district's mean signed residual around the contemporaneous weighted median. During the GFC recession, Dallas and Kansas City lie farthest on the tight side of the distribution. In the ZLB recovery, Minneapolis takes that position while San Francisco remains on the loose side. The COVID shock is more polarized: New York and San Francisco lie well below the median, while Kansas City, Minneapolis, and Richmond lie above it. The distribution narrows after the ZLB and during reopening, but its composition remains structured rather than uniform. The figure identifies who contributes to the episode averages; it does not turn the episodes into treatments.

FIGURE 5. Named District Profiles across Historical Episodes



Note: Cells report each district's mean raw UV-gap residual around the contemporaneous labor-force-weighted district median, in gap percentage points. Positive values indicate tighter conditions than the monthly district median; negative values indicate looser conditions. GFC recession is December 2007–June 2009; ZLB recovery is July 2009–December 2015; post-ZLB/pre-COVID is January 2016–December 2019; COVID shock is March–December 2020; and reopening/inflation is January 2021–December 2025, excluding unusable October 2025. Appendix Figure D1 aligns the signed and absolute residuals with threshold incidence and contribution shares. Episode comparisons are descriptive, not causal.

5.2. Prior-window demeaning and concentration

The matched-support comparison changes the object from raw district location to variation beyond the recent district-specific mean. Even after that adjustment, the 25-basis-point crossing occurs in 77.2 percent of eligible months, affects 2.5 districts on average, and reaches a 35-month maximum run in Dallas. The median positive district spell lasts 2 months. This companion narrows the claim to district variation beyond recent location; it uses current-vintage data, does not reconstruct what was known in real time, and does not replace the raw information-loss estimand.

The matched support begins in January 2006 after the 60-month burn-in and ends in September 2025. Although November and December 2025 remain usable for the raw estimand, their preceding 60-month calendars contain the missing October 2025 LAUS month and therefore fail the consecutive-calendar requirement. This is why the matched sample contains 237 months.

The result is not an artifact of one weighting choice or one omitted district. For the full sample, equal-district and capped-weight district exposure at 25 basis points are 31.9 and 31.8 percent, compared with 32.3 percent under labor-force weights. Across all twelve leave-one-district calculations, the range is 28.7 to 33.5 percent. The largest state-to-district cell, California–San Francisco, accounts for 11.45 percent of the full-sample weighted absolute-distance burden on average. These complete influence grids disclose concentration without redefining the estimand around an ex post deletion.

6. Measurement Checks and Interpretation Boundaries

The aggregation result could be distorted if the state inputs fail to reconcile to their national counterparts or if the nonlinear unemployment–vacancy construction creates the apparent geographic pattern. Two measurement checks address those concerns before I state the boundaries of the exercise.

First, the state inputs reconcile closely to their national counterparts before the nonlinear UV benchmark is formed. Across 299 months, the labor-force-weighted state unemployment rate differs from national unemployment by 0.0003 percentage points on average and 0.0918 RMS; the corresponding vacancy differences are 0.0033 and 0.0466 percentage points. These are separate reconciliations of independently constructed official-statistics products, not an imposed identity.

Second, repeating the exact accounting with unemployment alone produces nearly the same allocation of squared loss. Within-district unemployment loss accounts for 55.84

percent of total state-to-national squared distance, between-district loss for 43.47 percent, and centering for 0.68 percent. The unemployment-only and primary UV-gap district rankings have a Spearman correlation of 0.860, and Minneapolis, Kansas City, and San Francisco occupy the first three positions under both. The geographic compression pattern is not specific to the vacancy input. The UV gap adds a joint unemployment–vacancy measure and the rule-equivalent calibration; it does not generate the compression pattern. This is a state-observed check using the same fractional allocator, not an independent validation or a county-level gap construction.[6]

These checks leave the raw estimand intact while showing where its magnitude can move. At 25 basis points, the observed national input exposes 33.0 percent of the labor force, compared with 32.3 percent around the absolute-distance-minimizing weighted median. The squared-distance comparison also leaves little room for scalar location to explain the gap. The squared-distance-minimizing state-supported mean is close to the observed national input, so centering accounts for only 0.69 percent of state-to-national squared distance. Reliability calibration lowers full-sample district exposure at 25 basis points from 32.3 to 24.2 percent. Combining reliability calibration with strictly prior district locations lowers matched-support exposure from 33.2 to 17.7 percent. Raw loss remains the primary description, prior-window demeaning is the leading companion, and reliability adjustments remain sensitivities rather than alternative headline estimands.

Three boundaries govern interpretation. First, the panel uses current-vintage public data and prior-month source labels, not the information set available to policymakers in real time. Second, county data allocate state gaps across split districts; they do not identify county vacancy gaps. Third, the reliability calibration uses published spot-error anchors under stated covariance and shrinkage assumptions. It is a sensitivity, not a correction for a fully estimated measurement-error process. These boundaries limit what the estimates represent without changing the accounting they validate.

7. Implications for Regional Measurement

The accounting separates two dimensions of regional fit. The location of a scalar shows whether it is centered; the geographic support determines how much of the underlying distribution remains visible when that location is evaluated. In this application, centering is minor relative to both geographic margins. Proximity to the center cannot establish that a national input represents the regional distribution well.

[6] Appendix Tables E1 to E3 report the complete reconciliations and unemployment-only results.

This distinction is central to regional measurement. Spatial aggregation has long been understood to alter measured regional relationships and multiregional models (Openshaw and Taylor 1979; Fotheringham and Wong 1991; Miller and Blair 1981). The ladder here shows how that problem carries into aggregate evaluation. Low dispersion among regional means is ambiguous because it can reflect similar local conditions or aggressive pooling within the regional units. Fit around a national scalar is more compressed still. A credible evaluation must report what the map suppresses, what survives between regions, and where the scalar sits relative to the surviving distribution.

The scale and zoning results make geography part of the measurement rather than background scenery. Across the three illustrative procedures, twelve regions retain 44–51 percent of labor-force-weighted state dispersion. The fixed-12 comparison separately shows that the grouping of states matters at the institutional count. These comparisons measure how much observed state variation different supports make visible. They do not supply the loss function or institutional costs needed to choose a regional system.

The measurement result has a direct informational implication. A reasonable national input need not describe every district equally well. Regional rule comparisons ask how common formulas translate heterogeneous conditions (Coibion and Goldstein 2012; Malkin and Nechio 2012), while heterogeneous-transmission studies ask whether a common policy action has different regional effects (Carlino and DeFina 1998, 1999; Owyang and Wall 2009). The regional distribution is the common object those questions inherit. If the objective is to observe cross-state dispersion rather than regional means, a twelve-region summary cannot substitute for state-level or comparably disaggregated information. This informational requirement is separate from the choice of a national policy rate.

The broader measurement lesson extends beyond this application. Whenever local observations are first grouped into regions and then summarized by a national statistic, the aggregate inherits the compression built into its geographic support. Evaluating that aggregate requires examining both its center and the distribution suppressed beneath it.

8. Conclusion

This paper asks how much regional labor-market information is lost when state-supported observations are represented by Federal Reserve district means and then evaluated against one national input. The answer cannot be inferred from the national input's location alone. It is well centered, accounting for only 0.69 percent of state-to-national squared distance, while 53.99 percent is lost within districts and 45.32 percent remains between them.

A similar compression pattern appears across the three illustrative procedures examined. Their twelve-region distributions retain median labor-force-weighted shares from 44.1 to 51.2 percent. Grouping also matters when the count stays fixed. On the common 237-month support, observed district distances of at least 25 basis points expose 33.2 percent of the labor force on average, or 20.6 percent after subtracting each district's strictly prior 60-month mean. Under the paper's illustrative calibration, the first sustained crossing below 25 rule-input basis points occurs between 18 and 21 regions, depending on the procedure. These crossings do not identify an optimal map or district count.

The estimates do not prescribe regional interest rates, redraw Federal Reserve districts, or identify welfare losses. They establish a narrower point about aggregate measurement. A national statistic can be correctly centered while concealing substantial regional variation. If the objective is to observe the cross-state distribution rather than regional means, state-level or comparably disaggregated information is needed alongside the national aggregate.

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Appendix A. Data, Timing, and Fractional Allocation

This appendix documents the inputs and institutional support behind the state–district cells. The tables preserve the distinction between source periods, current-vintage construction, and county allocation.

TABLE A1. Measurement Inputs and Geographic Construction Sources

Object	Source	Frequency/unit	Role in construction
u_{it}	BLS Local Area Unemployment Statistics	Monthly; percent of state labor force; seasonally adjusted	State unemployment input in x_{it}.
L_{it}	BLS Local Area Unemployment Statistics	Monthly; persons; seasonally adjusted	State labor-force weights for state and district aggregation.
$v_{i,t-1}$	BLS State JOLTS	Published monthly job-openings rate, percent; source period $m-1$	Prior-period state rate in the unemployment-vacancy benchmark; vacancy levels are outside the baseline.
u_t	BLS national unemployment rate	Monthly; percent of national labor force	National unemployment input in the baseline BLS/JOLTS benchmark.
j_{t-1}	BLS JOLTS	Published monthly job-openings rate, percent; source period $m-1$	Prior-period national rate in the baseline BLS/JOLTS benchmark; vacancy levels are outside the baseline.
NROU	Congressional Budget Office	Quarterly percent, linearly interpolated to monthly frequency	Long-run natural-rate comparison benchmark.
NROUST	Congressional Budget Office	Quarterly percent, linearly interpolated to monthly frequency	Short-term natural-rate comparison benchmark.
County-district map	Federal Reserve Bank of Kansas City TB 19-01 data archive (2019–06–06)	County-level district identifiers	Maps counties to Federal Reserve districts and identifies split-state cells.
Split-state population weights	Census 2019 county population estimates	Persons	Baseline allocation weights inside split states.
Split-state labor-force weights	BLS LAUS county labor force	Persons	Alternative allocation weights inside split states.

Note: Sources cover the variables and geographic mappings used to construct the state, national, and district measures. Window labels use the NBER recession indicator `USRECM`, the Federal Reserve target-range lower limit `DFEDTARL`, and the documented July 2009–December 2015 ZLB recovery period.

TABLE A2. Summary Statistics, Full Available Measurement Sample

Variable	Unit	N	Mean	SD	P10	Median	P90
Panel A. State-month variables and constructed benchmark							
Observed state unemployment u_{it}	State-month	15,249	5.3	2.2	3.1	4.8	8.2
State job-openings rate $v_{i,t-1}$	State-month	15,249	3.8	1.4	2.3	3.5	5.8
State unemployment-vacancy benchmark u^*_{it}	State-month	15,249	4.3	0.7	3.4	4.1	5.2
State labor-market gap $x_{it} = u^*_{it} - u_{it}$	State-month	15,249	-1.1	1.9	-3.6	-0.7	1.0
Panel B. National monthly variables and candidate benchmarks							
National unemployment u_t	Month	299	5.7	2.0	3.7	5.1	9.0
National job-openings rate j_{t-1}	Month	299	3.7	1.3	2.4	3.3	5.4
Baseline national gap x^0_t	Month	299	-1.3	1.8	-4.4	-0.9	0.6
CBO long-run natural-rate gap	Month	228	-1.1	1.7	-4.0	-0.6	0.6
CBO short-term natural-rate gap	Month	228	-0.9	1.5	-3.3	-0.5	0.7
Panel C. District-month measurement objects							
District labor-market gap x_{dt}	District-month	3,588	-1.2	1.8	-3.8	-0.9	0.8
District-minus-national rule-input gap $100\phi_x(x_{dt} - x^0_t)$	District-month	3,588	4.9	28.8	-28.3	3.4	38.0
Absolute district-minus-national rule-input gap $100\phi_x\lvert x_{dt} - x^0_t\rvert$	District-month	3,588	21.7	19.5	3.0	16.8	47.1
District p90-p10 spread	Month	299	66.4	34.8	30.4	58.1	123.3

Note: The full available measurement sample runs from January 2001 through December 2025; October 2025 has no usable state benchmark observation. The state benchmark pairs LAUS u_{it} with the published State JOLTS rate $v_{i,t-1}$, and the national benchmark pairs national unemployment u_t with the published JOLTS rate j_{t-1}. Thus January 2001 uses December 2000 JOLTS. This reference-period alignment concerns observation months, not release availability. Vacancy levels are outside the baseline. State and national variables are percentage points except job-openings rates, which are also percentages. District rule-input gaps and the district p90-p10 spread are measured in rule-input basis points. The CBO long-run and short-term natural-rate gaps use linearly interpolated monthly CBO series and are reported over their comparison-sample coverage.

Together, the four tables fix the measurement and geographic support used by the rest of the appendix. With those inputs held constant, Appendix B turns from construction to the mechanics of representation loss.

TABLE A3. Split-State Allocation Schematic

State/DC unit	Federal Reserve district allocation
Connecticut	Boston 73.5%; New York 26.5%
Illinois	Chicago 88.7%; St. Louis 11.3%
Indiana	Chicago 85.4%; St. Louis 14.6%
Kentucky	Cleveland 44.0%; St. Louis 56.0%
Louisiana	Atlanta 79.4%; Dallas 20.6%
Michigan	Chicago 97.0%; Minneapolis 3.0%
Mississippi	Atlanta 61.9%; St. Louis 38.1%
Missouri	St. Louis 67.7%; Kansas City 32.3%
New Jersey	New York 68.6%; Philadelphia 31.4%
New Mexico	Kansas City 67.5%; Dallas 32.5%
Pennsylvania	Philadelphia 74.7%; Cleveland 25.3%
Tennessee	Atlanta 77.1%; St. Louis 22.9%
West Virginia	Cleveland 8.2%; Richmond 91.8%
Wisconsin	Chicago 84.9%; Minneapolis 15.1%

Note: Rows list the state/DC units split across Federal Reserve districts in the baseline allocator. Shares are 2019 Census county-population shares used to allocate state labor force and state gaps to district cells. They are allocation weights for state-level unemployment-vacancy gaps, not county-level vacancy-gap estimates.

TABLE A4. Federal Reserve District Geography and Allocation Accounting

Statistic	Value
County rows in district map	3,142
State/DC units	51
Split state/DC units	14
Nonzero state-district allocation cells	65
Share of 2019 population in split states	27.2%
Minimum state population coverage in mapping	100.0%
Split-state county rows with LAUS labor-force data	1,009
Split-state county LAUS labor-force coverage	100.0%

Note: County rows are the Census county universe matched to the Federal Reserve district county file. Split-state shares use 2019 Census county population in the baseline allocator. The LAUS rows show coverage for alternative split-state weights based on county labor-force data.

Appendix B. Representation-Loss Mechanics

This section distinguishes two loss functions that perform different jobs in the paper. The squared-distance identity accounts exactly for variation lost within districts, variation retained between districts, and centering relative to the national input. The absolute-distance problem instead supplies the best common scalar used in the materiality analysis; it is not another component of the squared-distance decomposition.

B.1. Squared-distance accounting

Tables B1 and B2 report the complete window accounting and a four-state sign example. The example makes the zoning interpretation explicit: lower between-region distance can reflect more variation averaged away within regions rather than better representation.

TABLE B1. Complete Squared-Distance Accounting

		RMS gap percentage points				Share of total squared distance		
Window	Months	Total	Within	Between	Centering	Within	Between	Centering
Full available	299	0.838	0.616	0.564	0.070	54.0%	45.3%	0.7%
Ordinary pre-2020	131	0.573	0.440	0.363	0.056	59.0%	40.1%	0.9%
GFC recession	19	1.084	0.807	0.720	0.070	55.4%	44.1%	0.4%
ZLB recovery	78	1.119	0.821	0.755	0.084	53.9%	45.5%	0.6%
GFC/ZLB	97	1.112	0.819	0.748	0.082	54.2%	45.3%	0.5%
COVID shock	10	1.651	1.229	1.098	0.115	55.3%	44.2%	0.5%
Reopening / inflation	59	0.576	0.364	0.442	0.063	39.9%	58.9%	1.2%
Top-quartile pre-COVID	57	1.308	0.964	0.880	0.085	54.3%	45.2%	0.4%

Note: Definitions, units, sample, centers, and weighting are identical to Table 2. Every monthly identity reconciles within 10^{-10} gap-percentage-point-squared units; window components are equal-month averages before roots and shares are computed. Squared distance is exactly additive across the three components. The absolute-distance materiality measure is a separate summary and is not additive across these components.

TABLE B2. Four-State Sign Example for the Squared-Distance Identity

Grouping	State values	District assignment	Total	Within	Between	Centering
Similar-state grouping	-1;-1;1;1	1;1;2;2	1.0	0.0	1.0	0.0
Mixed-state grouping	-1;-1;1;1	1;2;1;2	1.0	1.0	0.0	0.0

Note: The fixture assigns equal weight to state values $(-1, -1, 1, 1)$ and centers on the common mean zero. Grouping like-valued states preserves all variation between regions; mixing opposite-valued states averages the same variation away within regions. Total squared distance remains one. Thus lower between-region distance is not by itself a better representation.

B.2. Absolute-distance common scalar

Table B3 documents the weighted-median solution used when the paper asks how far district conditions lie from one common input. These diagnostics validate the scalar behind the threshold summaries without changing the estimand in the exact accounting.

TABLE B3. Optimized Common-Input Weighted-Median Diagnostics

Window	Months	Optimal-scalar location				Kink concentration	
		Mean loc.	Mean abs. loc.	p10–p90 range	Median–mean	Kink weight >15%	Modal kink (share)
Full sample	299	-4.0	6.3	[-15.0, 4.2]	-2.4	14%	Atlanta (20%)
Pre-2020	228	-5.4	6.9	[-16.1, 3.2]	-3.8	18%	Atlanta (26%)
GFC/ZLB	97	-9.4	10.2	[-20.9, 0.4]	-7.5	3%	Atlanta (37%)
Pre-2020 top-spread	57	-10.5	11.4	[-23.6, 0.5]	-8.6	2%	Atlanta (37%)
Ex-COVID	289	-4.3	6.3	[-15.0, 4.2]	-2.7	15%	Atlanta (20%)

Note: The optimized common input is the within-month weighted district median measured relative to the baseline national input, in rule-input basis points. Mean absolute optimized input reports the average absolute location of that median. The p10–p90 entry is the descriptive range across monthly optimized inputs within the stated window; it is not an uncertainty interval. Median-minus-mean compares the weighted-median minimizer of mean absolute distance with the weighted district mean in the same month. Kink weight is the labor-force share of the district at the weighted-median kink; the share above 15 percent records months in which that district is large enough for the absolute-distance objective to hinge visibly on one district. The modal kink district is the district most often located at the weighted-median kink, with its share of months in parentheses.

The two sets of mechanics therefore answer separate questions: the first locates where cross-sectional variation is lost, while the second measures the remaining district distribution around its best common scalar. Appendix C now asks how coefficient calibration, geographic scale, and zoning change the display of those losses.

Appendix C. Coefficient Calibration, Geographic Scale, and Zoning

This section separates three choices that should not be read as alternative estimates of one parameter. Coefficient calibration changes the units used to display a given gap. Geographic scale changes the number of regional means. Zoning changes which states are grouped together while holding that count fixed.

C.1. Rule-coefficient calibration

Table C1 records the prespecified conversion from gap-percentage-point distances to the paper's illustrative 25- and 50-basis-point thresholds. It makes the unit conversion transparent without estimating or selecting a policy-rule coefficient from the incidence results.

TABLE C1. Illustrative Rule-Coefficient Calibration

ϕ_x	Entries shown as 25 bp / 50 bp				Months	Support
	Gap threshold (gap pp)	Exposed share	Affected districts	Months with any crossing		
State-to-district compression: cells around district means						
0.25	1.00 / 2.00	8.6% / 1.4%	5.4 / 1.4	98.7% / 50.2%	299	Full
0.50	0.50 / 1.00	27.0% / 8.6%	9.6 / 5.4	100.0% / 98.7%	299	Full
1.00	0.25 / 0.50	47.8% / 27.0%	11.3 / 9.6	100.0% / 100.0%	299	Full
District-to-common-input distance: districts around weighted median						
0.25	1.00 / 2.00	8.5% / 0.6%	1.2 / 0.1	37.8% / 6.7%	299	Full
0.50	0.50 / 1.00	32.3% / 8.5%	4.0 / 1.2	94.0% / 37.8%	299	Full
1.00	0.25 / 0.50	57.2% / 32.3%	7.0 / 4.0	100.0% / 94.0%	299	Full
District-to-common-input distance: 60-month matched support						
0.25	1.00 / 2.00	10.5% / 0.8%	1.5 / 0.1	43.9% / 8.4%	237	Prior matched
0.50	0.50 / 1.00	33.2% / 10.5%	4.1 / 1.5	92.4% / 43.9%	237	Prior matched
1.00	0.25 / 0.50	57.1% / 33.2%	6.9 / 4.1	100.0% / 92.4%	237	Prior matched
History-adjusted district distance: matched support						
0.25	1.00 / 2.00	3.6% / 0.3%	0.5 / 0.0	24.5% / 1.3%	237	Prior matched
0.50	0.50 / 1.00	20.6% / 3.6%	2.5 / 0.5	77.2% / 24.5%	237	Prior matched
1.00	0.25 / 0.50	43.1% / 20.6%	5.3 / 2.5	99.6% / 77.2%	237	Prior matched

Note: The table reports the complete full-sample coefficient grid for state-to-district compression, district-to-common-input distance, its matched-support counterpart, and the history-adjusted companion. Each paired entry reports the value at the 25-basis-point threshold followed by the value at the 50-basis-point threshold. For each prespecified ϕ_x, the gap-threshold entry gives the absolute residual in gap percentage points required for those rule-equivalent contributions. No coefficient is estimated, selected from incidence, or interpreted as the response coefficient for a complete policy rule. The scaled quantities are illustrative units, not realized policy rates, policy errors, district recommendations, or welfare losses. Centers and supports follow Table D1.

C.2. Geographic procedures and scale

The next three tables move from construction to comparison. They first define the three illustrative procedures and their conditional support, then report their fixed-12 distributions and procedure-specific scale thresholds, and finally summarize how retained dispersion changes across ranges of region counts. Each procedure induces its own distribution, so the tables do not pool or rank the procedures as competing estimates.

TABLE C2. Construction of Three Illustrative Geographic Procedures

Procedure	Construction and induced distribution
Global tree cutting	Global unweighted spanning trees followed by uniform cuts of $K - 1$ tree edges.
Population-weighted frontier growth	Population-weighted starting nodes and local frontier-pair growth under the procedure's induced order.
Anchored edge-order joining	Uniform starting-node sets and randomized edge orders joined by an anchor-preserving Kruskal rule.

Note: The three procedures are illustrative and not exhaustive. They induce different probability weights over feasible connected partitions, and there is no probability weighting across procedures. All three use the same graph of 51 state/DC nodes: shared land borders plus Alaska–Washington to connect Alaska through the Pacific Northwest, California–Hawaii to connect Hawaii through the Pacific coast, and District of Columbia links to Maryland and Virginia along its two state boundaries. The support imposes the one-sided 2019 labor-force-share cap $\max\{3/K, s_{\max} + 0.002\}$, where $s_{\max}$ is the largest single-state share; there is no positive lower-share bound. These rules define the conditional feasible support.

TABLE C3. Fixed-12 Distributions and Scale Thresholds

Procedure	LF median [p10, p90]	Equal median [p10, p90]	First sustained K below 25 bp	Fed pct., LF	Fed pct., equal
Global tree cutting	44.1% [33.8%, 52.8%]	68.5% [58.5%, 77.0%]	21	70.3%	5.3%
Population-weighted frontier growth	51.2% [43.6%, 58.3%]	57.7% [48.9%, 67.0%]	18	29.3%	37.6%
Anchored edge-order joining	45.7% [35.7%, 54.1%]	66.5% [56.4%, 75.3%]	21	62.5%	8.4%

Note: Each stochastic $K = 2$–50 distribution is generated separately rather than as a nested refinement of the $K = 12$ maps, and its quantiles follow the distribution induced by that procedure; the $K = 1$ and $K = 51$ endpoints are analytic. Each stochastic cell uses its registered first 10,000 accepted histories, with cumulative checkpoints at 1,000, 2,500, 5,000, and 10,000 histories and seed bases 2026101000, 2026201000, and 2026301000 plus K. Duplicate histories remain in the estimand because it is the distribution induced by each procedure; cell-specific attempts, rejection and duplicate counts, Monte Carlo checkpoints, unique-partition sensitivity, and separately certified finite-support cells are recorded in the production ledgers. The whole-state Federal Reserve analogue is distinct from the synthetic $K = 12$ distributions and from the paper's fractional Federal Reserve accounting. The sustained-threshold column is the first K after which the labor-force median remains below 25 basis points through $K = 50$, with $K = 51$ analytically zero; it is not an optimum or an institutional recommendation.

TABLE C4. Retained-Dispersion Gains across Geographic Scale

Procedure	LF, K = 3–12	LF, K = 12–50	Equal, K = 3–12	Equal, K = 12–50
Global tree cutting	4.27	1.46	3.21	0.82
Population-weighted frontier growth	4.68	1.27	4.79	1.11
Anchored edge-order joining	4.33	1.42	4.04	0.87

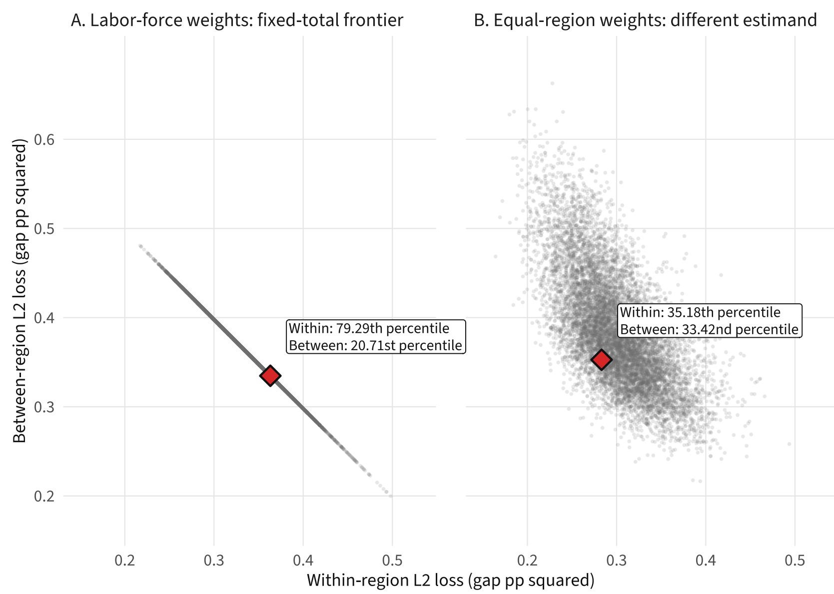
Note: Entries are the average percentage-point gain in the retained share of state/DC dispersion for each added region over the indicated range. Labor-force and equal-region weighting define distinct summaries. All early-range gains exceed their corresponding later-range gains, a descriptive comparison that does not establish global concavity, an optimal map, or an institutional recommendation.

Across the three procedures, the first sustained K below 25 rule-input basis points ranges from 18 to 21. The early- and late-range comparisons report the average percentage-point gain in the retained share from each additional region. These are scale comparisons, not estimates of an optimal region count or an institutional recommendation. The fixed-count analysis that follows isolates zoning.

C.3. Fixed-12 zoning and robustness

Figure C1 locates the whole-state Federal Reserve analogue within one tighter balanced-map design. This is a conditional zoning comparison at twelve regions, distinct from both the fractional Federal Reserve accounting and the three scale distributions above.

FIGURE C1. Fixed-12 Map Context



Note: Gray points are sampled contiguous partitions of 51 states/DC into twelve regions under the tighter balanced-map design. The red diamond is the whole-state Federal Reserve analogue. Values are full-sample mean squared gap-percentage-point losses. In Panel A, labor-force weighting fixes total state variation, making the within–between line an exact frontier and the two marginal percentiles complementary. Panel B applies equal weight to constructed regions, changing the effective state weights and the estimand. The whole-state analogue is not the fractional split-state baseline, and neither panel ranks map quality or welfare.

Under labor-force weights, the whole-state Federal Reserve analogue lies at the 79.29th percentile of within-region loss and the complementary 20.71st percentile of between-region loss. The zero joint lower-left count is mechanical because every map lies on the same frontier. Under equal-region weights, the analogue lies at the 35.18th and 33.42nd marginal percentiles, and 2.42 percent of maps lie in the joint lower-left set. These locations are a conditional fixed-12 zoning sensitivity, not validation of the broader three-procedure scale result.

TABLE C5. Algorithm-Conditional Fixed-12 Map Location

Weighting	Location	Mean squared distance	Percentile	MC SE	Wilson 95% CI
Labor force	Within-region squared distance	0.3632	79.29	0.405	[78.48, 80.07]
Labor force	Between-region squared distance	0.3347	20.71	0.405	[19.93, 21.52]
Equal region	Within-region squared distance	0.2832	35.18	0.478	[34.25, 36.12]
Equal region	Between-region squared distance	0.3527	33.42	0.472	[32.50, 34.35]
Equal region	Joint lower-left	–	2.42	0.154	[2.14, 2.74]

Note: The table locates the whole-state Federal Reserve analogue within the sampled distribution of contiguous 12-region partitions. Under labor-force weights, within- and between-region squared distances exhaust the same fixed total for every map, so the two marginal percentiles are complementary descriptions of one frontier location; no labor-force joint lower-left result is reported as additional evidence. Under equal-region weights, the map changes the effective weights on underlying states, so total distance can vary and the joint lower-left row is a distinct algorithm-conditional description. Marginal percentiles are the shares of sampled maps with a component no larger than observed. Monte Carlo standard errors use Jeffreys smoothing; brackets give Wilson 95% intervals. Production uses 10,000 unique accepted maps from 14,601 attempts with zero duplicates (seed 2026073003), after 1,410 share-cap and 3,191 final-bound rejections; no frontier-exhaustion or connectivity rejections occurred. Cumulative checkpoints were recorded at 1,000, 2,500, 5,000, and 10,000 accepted maps. Mean squared distance is measured in gap-percentage-point-squared units over the full sample. Results are conditional on the augmented graph, generator, 12 regions, share bounds, and weighting scheme. The whole-state object is not the paper's fractional split-state baseline. These locations rank neither map quality, welfare, nor optimality.

Tables C6 and C7 then move from map location to the leading sample, allocation, and influence objections. They are robustness checks on the observed accounting, not additional map quality criteria.

TABLE C6. Sample-Period and Split-State Allocation Checks

Window	Statistic	Value
Sample restriction		
Full vs pre-2020	Full-sample lower bound	20.9 bp
Full vs pre-2020	Pre-2020 lower bound	20.8 bp
Full vs pre-2020	Pre-2020 minus full lower bound	-0.1 bp
Full vs pre-2020	Pre-2020 minus full p90-p10 spread	+1.2 bp
Top-spread months	Pre-2020 minus full-sample lower bound	-0.1 bp
Split-state allocator sensitivity		
Top-spread months	P90-p10 range across county allocators	0.03 bp
Top-spread months	Remaining-mismatch range across county allocators	0.03 bp
Top-spread months	Minimum correlation with baseline allocator	0.999996
Top-spread months	Selected-month overlap with baseline allocator	100%

Note: Sample-restriction rows compare the full available measurement sample through December 2025 with the January 2001–December 2019 pre-2020 restriction and with top-spread windows selected within each sample. The allocator rows compare the baseline 2019 county-population allocation with static county-labor-force and monthly county-labor-force allocations. Remaining mismatch is the allocator-specific common-input lower-bound measure.

TABLE C7. Influential-Region and State-to-District Checks

Window	Statistic	Value
Leave-one-out influence		
GFC/ZLB window	Baseline district p90-p10 spread	95.3 bp
GFC/ZLB window	P90-p10 after excluding Dallas district	80.9 bp
GFC/ZLB window	P90-p10 after excluding Texas-Dallas cell	88.2 bp
State-to-district compression		
Pre-2020 sample	District/state p90-p10 ratio	0.68
GFC/ZLB window	District/state p90-p10 ratio	0.68
Top-spread months	District/state p90-p10 ratio	0.68

Note: Leave-one-out rows report GFC/ZLB window p90-p10 spreads after removing the most influential district or the largest state-district cell in that district; the baseline GFC/ZLB window p90-p10 spread is 95.3 rule-input basis points. State-to-district ratios divide district p90-p10 spread by state p90-p10 spread in the same window.

The sequence matters: coefficient calibration supplies units, geographic scale determines how many regional summaries remain, and fixed-12 zoning determines which observations those summaries combine. Appendix D turns from that geographic accounting to the incidence and persistence of the variation that remains.

Appendix D. Materiality, Incidence, and Persistence

This section moves from aggregate incidence to named district profiles and then to influence. The order keeps the headline materiality objects distinct from the exhaustive state–district-cell inventory that supports traceability but does not carry the paper's central claim.

D.1. Threshold incidence and persistence

Table D1 expands the main-text materiality results across windows, thresholds, supports, and the history-adjusted companion. Read its four panels as separate absolute-distance summaries: state-to-district compression, raw district distance, the matched-support raw comparison, and the prior-window-demeaned comparison. These quantities are not added to the exact squared-distance components in Appendix B.

The grid distinguishes whether a threshold crossing is broad, recurrent, or long-lived under each stated construction. It establishes the aggregate incidence question before naming the districts behind the episode averages.

TABLE D1. Complete 25/50-Basis-Point Materiality Grid

Window	Cutoff (bp)	Mo.	Level: Mean absolute distance (gap pp)	Breadth: Exposed share	Breadth: Affected districts	Recurrence: Any-month crossing	Persistence: Longest run	Persistence: Median spell
State-to-district compression: cells around district means								
Full available	25	299	0.393	27.0%	9.6	100.0%	212	2.0
	50			8.6%	5.4	98.7%	170	2.0
Ordinary pre-2020	25	131	0.308	20.9%	9.8	100.0%	83	2.0
	50			4.3%	4.5	99.2%	78	1.0
GFC recession	25	19	0.549	40.3%	9.6	100.0%	19	4.0
	50			18.6%	7.9	100.0%	19	5.0
ZLB recovery	25	78	0.565	41.5%	10.9	100.0%	78	2.0
	50			16.2%	8.2	100.0%	78	2.0
GFC/ZLB	25	97	0.562	41.3%	10.7	100.0%	97	2.0
	50			16.6%	8.1	100.0%	97	2.0
COVID shock	25	10	0.789	52.4%	11.4	100.0%	10	3.0
	50			26.1%	9.4	100.0%	10	2.0
Reopening / inflation	25	59	0.244	13.4%	7.0	100.0%	40	2.0
	50			2.2%	2.4	94.9%	16	2.0
Top-quartile pre-COVID	25	57	0.690	51.0%	10.9	100.0%	53	2.0
	50			23.2%	9.1	100.0%	53	2.0
District-to-common-input distance: districts around weighted median								
Full available	25	299	0.418	32.3%	4.0	94.0%	117	1.0
	50			8.5%	1.2	37.8%	79	1.0
Ordinary pre-2020	25	131	0.285	20.1%	2.8	88.5%	40	1.0
	50			0.3%	0.1	6.9%	4	1.0
GFC recession	25	19	0.581	51.4%	6.6	100.0%	19	8.0
	50			20.8%	3.2	84.2%	16	3.5
ZLB recovery	25	78	0.595	48.5%	6.1	100.0%	78	2.0
	50			20.0%	3.1	92.3%	71	1.0
GFC/ZLB	25	97	0.592	49.1%	6.2	100.0%	97	2.0
	50			20.1%	3.1	90.7%	79	1.0
COVID shock	25	10	0.877	62.1%	7.4	100.0%	10	1.0
	50			41.6%	4.4	90.0%	8	4.0
Reopening / inflation	25	59	0.357	27.5%	2.7	98.3%	20	1.5
	50			2.0%	0.2	11.9%	4	3.0
Top-quartile pre-COVID	25	57	0.737	63.9%	7.6	100.0%	53	2.0
	50			28.7%	4.2	100.0%	53	1.0

TABLE D1 (continued)

Window	Cutoff (bp)	Mo.	Level	Breadth		Recurrence	Persistence	
			Mean absolute distance (gap pp)	Exposed share	Affected districts	Any-month crossing	Longest run	Median spell
District-to-common-input distance: 60-month matched support								
Full available	25	237	0.438	33.2%	4.1	92.4%	117	1.0
	50			10.5%	1.5	43.9%	79	1.0
Ordinary pre-2020	25	71	0.237	12.9%	1.9	78.9%	28	1.5
	50			0.0%	0.0	0.0%	0	0.0
GFC recession	25	19	0.581	51.4%	6.6	100.0%	19	8.0
	50			20.8%	3.2	84.2%	16	3.5
ZLB recovery	25	78	0.595	48.5%	6.1	100.0%	78	2.0
	50			20.0%	3.1	92.3%	71	1.0
GFC/ZLB	25	97	0.592	49.1%	6.2	100.0%	97	2.0
	50			20.1%	3.1	90.7%	79	1.0
COVID shock	25	10	0.877	62.1%	7.4	100.0%	10	1.0
	50			41.6%	4.4	90.0%	8	4.0
Reopening / inflation	25	57	0.357	27.7%	2.7	98.2%	20	1.5
	50			2.1%	0.2	12.3%	4	3.0
Top-quartile pre-COVID	25	57	0.737	63.9%	7.6	100.0%	53	2.0
	50			28.7%	4.2	100.0%	53	1.0
History-adjusted district distance: matched support								
Full available	25	237	0.298	20.6%	2.5	77.2%	35	2.0
	50			3.6%	0.5	24.5%	14	1.0
Ordinary pre-2020	25	71	0.219	9.6%	1.3	74.6%	20	1.0
	50			0.7%	0.1	8.5%	3	1.0
GFC recession	25	19	0.449	39.3%	4.3	100.0%	19	6.0
	50			11.9%	1.7	89.5%	8	2.5
ZLB recovery	25	78	0.383	33.0%	4.1	98.7%	26	2.0
	50			3.4%	0.5	32.1%	11	1.0
GFC/ZLB	25	97	0.396	34.3%	4.2	99.0%	28	2.0
	50			5.1%	0.7	43.3%	14	1.0
COVID shock	25	10	0.706	55.5%	6.1	100.0%	9	3.0
	50			28.6%	3.2	80.0%	7	2.0
Reopening / inflation	25	57	0.165	5.8%	0.6	40.4%	14	1.5
	50			0.3%	0.0	3.5%	1	1.0
Top-quartile pre-COVID	25	57	0.465	44.5%	5.3	100.0%	26	3.0
	50			7.8%	1.1	63.2%	14	1.0

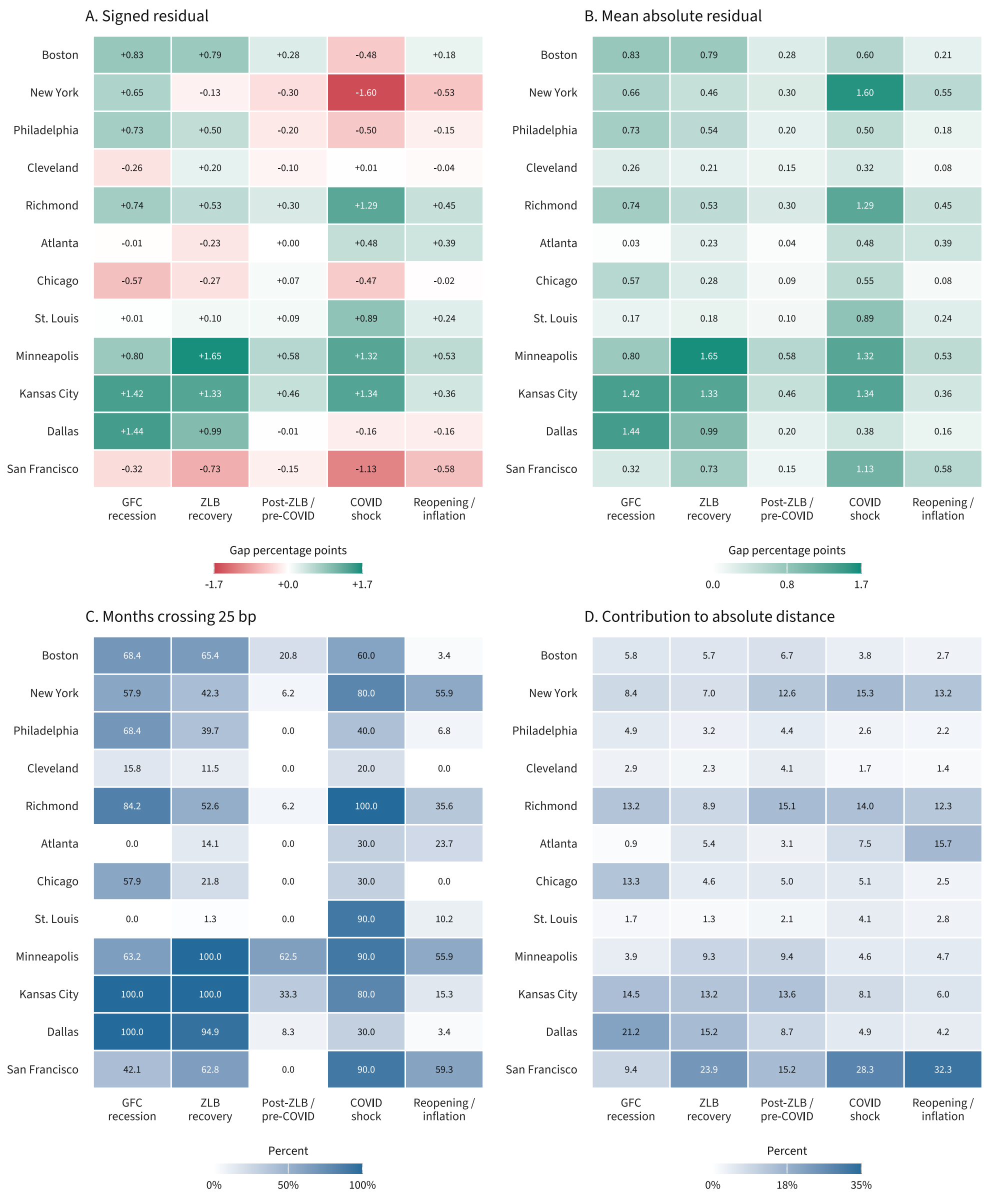
Note: The two sheets print every registered threshold separately; blank level cells on 50-bp rows repeat the window value printed immediately above. Mean absolute distance is the weighted mean absolute residual in gap percentage points and is not added to the exact squared-distance components. The 25- and 50-basis-point rows correspond to absolute residual thresholds of 0.50 and 1.00 gap percentage points under the display calibration $\phi_x = 0.50$. State-to-district rows use state-district-cell units centered on district means; district-to-common-input rows use district units centered on the contemporaneous weighted median. The history-adjusted companion uses 60 strictly prior consecutive eligible calendar months on identical matched support. Longest run is the largest district-specific consecutive crossing; median spell is the median across positive district spells and therefore may be a half month. Rule-equivalent contributions are a coefficient calibration, not realized rates or policy errors.

D.2. District profiles across episodes

Figure D1 presents four aligned district-by-episode matrices: signed residuals, absolute residuals, crossing incidence, and contribution shares. The shared ordering makes direction, magnitude, recurrence, and burden comparable without turning the historical episodes into treatments.

The episode atlas identifies who contributes to the remaining distribution, not whether one weighting rule or one influential unit creates it. The final cluster addresses that narrower robustness question.

FIGURE D1. Named District Profile across Historical Episodes

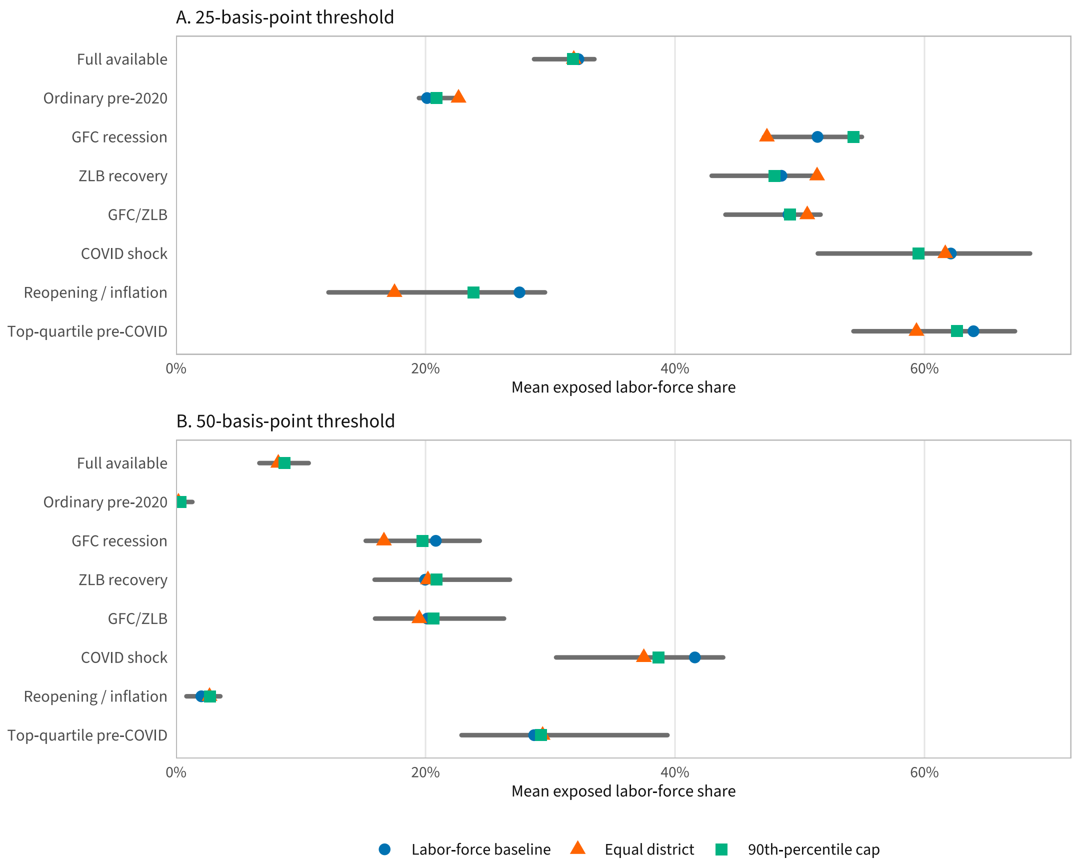


Notes: Panels A and B report raw district UV-gap residuals around each month's labor-force-weighted district median, in gap percentage points; positive signed values indicate tighter conditions than the monthly median. Panel C reports the percentage of episode months in which the district's absolute residual is at least 0.50 gap percentage points, equivalent to 25 basis points under the display calibration $\phi_x = 0.50$. Panel D reports the episode average of the district's monthly labor-force-weighted share of total absolute district distance from the weighted median; its twelve district shares sum to 100 percent within each episode. Color follows measurement units: Panels A and B use the gap-percentage-point red–white–teal family, with Panel A centered at zero because sign carries meaning and Panel B using its nonnegative white-to-teal half. Panels C and D use the same white-to-blue percent palette. The percent panels retain panel-specific ranges because their statistics have different maxima. Every cell is labeled: percentage panels omit the percent sign inside cells. GFC recession is December 2007–June 2009; ZLB recovery is July 2009–December 2015; post-ZLB/pre-COVID is January 2016–December 2019; COVID shock is March–December 2020; reopening/inflation is January 2021–December 2025 excluding unusable October 2025. The episode comparisons are descriptive and do not identify causal effects.

D.3. Weighting and influence

Figure D2 comes first because it tests the labor-force, equal-district, capped-weight, and leave-one-district constructions used to interpret the headline incidence. Table D2 then shows how quickly absolute-distance burden accumulates, and Table D3 identifies the cells at the registered rank milestones. Table D4 provides the complete 65-cell ranked inventory behind state-to-district compression. The ledger is lookup documentation: exposure, absolute-distance contribution, squared-distance contribution, and threshold activity remain distinct columns.

FIGURE D2. District Weighting and Leave-One-District Influence



Notes: Panel A reports the 25-basis-point threshold; Panel B reports the 50-basis-point threshold. Points report mean exposed labor-force shares after recomputing residuals around each weighting-specific contemporaneous median. Gray segments are deterministic minima and maxima across all twelve named leave-one-district recomputations after renormalization; they are not confidence intervals. The cap truncates contemporaneous district weights at the 90th percentile and renormalizes them. No omitted district is selected by its result. Thresholds and units follow Tables 3 to 5.

TABLE D2. Concentration of Named State-District-Cell Burden, Full Sample

Milestone	Cells included	Cumulative absolute-distance burden	Cumulative exposure
Largest cell	1	11.4%	11.8%
Top 10	10	45.4%	36.0%
Top 14	14	54.9%	49.0%
Top 20	20	66.3%	57.6%
All 65	65	100.0%	100.0%

Note: Cumulative shares are reported at predeclared rank milestones. Cells are ranked only by their full-sample mean share of labor-force-weighted absolute state-to-district distance; exposure and squared-distance rankings may differ.

TABLE D3. Boundary Cells at Registered Concentration Milestones, Full Sample

Rank	Boundary cell	Cell burden	Cell exposure
1	CA - San Francisco	11.45%	11.85%
10	IA - Chicago	2.93%	1.07%
14	NY - New York	2.15%	6.15%
20	ID - San Francisco	1.77%	0.52%
65	WV - Cleveland	0.08%	0.04%

Note: Each row identifies the cell at the corresponding registered rank milestone in Table D2. These are deterministic boundary cells, not a selected list of favorable or adverse examples. The complete ledger follows in Table D4.

TABLE D4. Complete Named State-District-Cell Influence Ledger, Full Sample

Rank	Cell	Exposure	Absolute-distance share	Squared-distance share	Active months	Active-distance share
					25 bp / 50 bp	
1	CA - San Francisco	11.85%	11.45%	7.15%	33.4% / 1.0%	6.5% / 0.1%
2	VA - Richmond	2.67%	4.61%	4.97%	58.2% / 21.4%	5.3% / 2.9%
3	MI - Chicago	3.05%	4.56%	5.48%	47.5% / 23.4%	5.2% / 6.2%
4	IL - Chicago	3.69%	4.10%	3.32%	32.1% / 1.7%	3.6% / 0.2%
5	FL - Atlanta	6.10%	4.07%	2.25%	10.7% / 2.0%	1.5% / 0.5%
6	NC - Richmond	3.01%	3.56%	3.38%	32.8% / 22.7%	3.0% / 3.9%
7	AZ - San Francisco	2.00%	3.52%	4.26%	62.2% / 20.7%	5.6% / 3.2%
8	UT - San Francisco	0.93%	3.44%	7.09%	92.6% / 53.2%	7.4% / 8.9%
9	WI - Chicago	1.68%	3.13%	3.30%	61.5% / 20.4%	3.7% / 1.8%
10	IA - Chicago	1.07%	2.93%	4.76%	71.2% / 44.5%	3.8% / 5.7%
11	GA - Atlanta	3.09%	2.64%	1.83%	20.4% / 1.7%	1.5% / 0.1%
12	WA - San Francisco	2.28%	2.57%	2.01%	38.1% / 8.7%	2.0% / 0.9%
13	SC - Richmond	1.42%	2.16%	2.42%	49.8% / 30.8%	2.4% / 3.9%
14	NY - New York	6.15%	2.15%	0.62%	1.7% / 0.0%	0.1% / 0.0%
15	MD - Richmond	1.98%	2.04%	1.57%	35.5% / 11.4%	1.7% / 0.9%

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TABLE D4 – continued

Rank	Cell	Exposure	Absolute-distance share	Squared-distance share	Active months	Active-distance share
					25 bp / 50 bp	
16	NJ - New York	2.01%	1.98%	1.53%	25.8% / 2.3%	1.3% / 0.3%
17	OR - San Francisco	1.27%	1.95%	2.12%	47.2% / 11.0%	2.5% / 1.6%
18	CO - Kansas City	1.80%	1.91%	1.50%	28.1% / 8.4%	1.3% / 0.5%
19	LA - Atlanta	1.05%	1.80%	2.37%	46.5% / 19.1%	2.5% / 1.2%
20	ID - San Francisco	0.52%	1.77%	3.38%	95.7% / 54.5%	4.2% / 5.5%
21	IN - Chicago	1.79%	1.54%	1.09%	18.1% / 1.7%	0.8% / 0.2%
22	HI - San Francisco	0.42%	1.51%	3.02%	90.0% / 64.5%	2.9% / 5.7%
23	CT - Boston	0.88%	1.28%	1.48%	41.5% / 15.7%	2.2% / 0.9%
24	TN - Atlanta	1.54%	1.24%	0.88%	21.1% / 2.0%	0.9% / 0.2%
25	NV - San Francisco	0.89%	1.21%	1.43%	40.5% / 23.1%	1.7% / 1.5%
26	PA - Philadelphia	3.06%	1.20%	0.33%	0.0% / 0.0%	0.0% / 0.0%
27	OH - Cleveland	3.73%	1.20%	0.29%	1.7% / 0.0%	0.0% / 0.0%
28	OK - Kansas City	1.15%	1.20%	0.84%	30.8% / 6.4%	0.8% / 0.2%
29	MA - Boston	2.29%	1.12%	0.43%	3.3% / 0.7%	0.1% / 0.0%
30	AL - Atlanta	1.41%	1.11%	0.68%	14.7% / 1.7%	0.5% / 0.1%
31	DC - Richmond	0.23%	1.10%	3.39%	97.0% / 83.9%	3.2% / 18.7%
32	NJ - Philadelphia	0.92%	1.05%	0.93%	33.1% / 13.4%	1.1% / 0.5%
33	PA - Cleveland	1.04%	1.03%	0.76%	28.1% / 10.0%	0.7% / 0.4%
34	MS - Atlanta	0.51%	1.02%	1.71%	55.2% / 18.4%	2.0% / 3.1%
35	NH - Boston	0.47%	0.97%	1.12%	69.6% / 30.4%	1.3% / 0.9%
36	NE - Kansas City	0.65%	0.95%	0.96%	48.8% / 27.1%	1.0% / 1.0%
37	MO - Kansas City	0.63%	0.89%	0.91%	48.5% / 20.4%	1.0% / 0.9%
38	MO - St. Louis	1.32%	0.79%	0.48%	6.0% / 0.3%	0.3% / 0.0%
39	TX - Dallas	8.18%	0.77%	0.05%	0.0% / 0.0%	0.0% / 0.0%
40	IL - St. Louis	0.47%	0.76%	0.84%	50.2% / 16.1%	1.0% / 0.5%
41	MN - Minneapolis	1.91%	0.73%	0.21%	3.3% / 0.0%	0.1% / 0.0%
42	AR - St. Louis	0.86%	0.72%	0.45%	16.1% / 9.0%	0.3% / 0.2%
43	NM - Kansas City	0.40%	0.66%	1.19%	36.1% / 16.1%	1.4% / 3.2%
44	KS - Kansas City	0.95%	0.64%	0.35%	7.7% / 0.0%	0.2% / 0.0%
45	WV - Richmond	0.47%	0.61%	0.67%	38.1% / 5.7%	1.0% / 0.4%
46	RI - Boston	0.36%	0.58%	0.78%	40.8% / 28.4%	0.6% / 0.9%
47	KY - St. Louis	0.73%	0.57%	0.39%	14.4% / 3.0%	0.3% / 0.1%
48	AK - San Francisco	0.23%	0.57%	1.09%	58.9% / 36.1%	1.1% / 2.1%
49	MS - St. Louis	0.31%	0.55%	0.79%	52.2% / 9.4%	1.1% / 1.0%
50	VT - Boston	0.22%	0.55%	0.77%	80.9% / 36.1%	0.9% / 0.8%
51	DE - Philadelphia	0.29%	0.50%	0.64%	54.2% / 17.4%	0.8% / 0.7%
52	ND - Minneapolis	0.25%	0.49%	0.63%	59.9% / 31.8%	0.6% / 0.6%
53	KY - Cleveland	0.57%	0.48%	0.39%	19.4% / 4.0%	0.4% / 0.2%
54	LA - Dallas	0.27%	0.47%	0.61%	46.2% / 10.7%	0.8% / 0.5%

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TABLE D4 – continued

Rank	Cell	Exposure	Absolute-distance share	Squared-distance share	Active months	Active-distance share
					25 bp / 50 bp	
55	ME - Boston	0.44%	0.45%	0.39%	17.1% / 4.0%	0.3% / 0.2%
56	SD - Minneapolis	0.29%	0.44%	0.46%	56.2% / 25.8%	0.5% / 0.4%
57	MI - Minneapolis	0.09%	0.39%	0.96%	84.3% / 63.2%	0.7% / 2.1%
58	MT - Minneapolis	0.33%	0.39%	0.38%	36.1% / 9.7%	0.4% / 0.4%
59	CT - New York	0.32%	0.33%	0.41%	24.7% / 4.7%	0.5% / 0.3%
60	NM - Dallas	0.19%	0.33%	0.44%	52.2% / 12.7%	0.6% / 0.7%
61	TN - St. Louis	0.46%	0.33%	0.19%	10.4% / 1.3%	0.1% / 0.0%
62	WI - Minneapolis	0.30%	0.32%	0.25%	34.1% / 9.7%	0.3% / 0.1%
63	WY - Kansas City	0.19%	0.30%	0.34%	55.5% / 26.8%	0.4% / 0.5%
64	IN - St. Louis	0.31%	0.25%	0.16%	16.1% / 3.0%	0.1% / 0.0%
65	WV - Cleveland	0.04%	0.08%	0.11%	64.2% / 25.1%	0.1% / 0.1%

Note: All 65 fractional state-district cells are shown, ranked before display by their full-sample mean share of the weighted absolute-distance burden within districts. Exposure is the mean cell labor-force weight. Absolute- and squared-distance shares are threshold-independent shares of the corresponding monthly state-to-district burden, averaged over months. Active months and active-distance shares are reported separately at the 25/50 thresholds. The California–San Francisco cell includes California's fractional exposure assigned to District 12; it is not county vacancy-gap evidence. Absolute- and squared-distance concentration measures remain distinct.

Having located the pattern across thresholds, episodes, weights, and named cells, Appendix E asks whether measurement choices or sample support change the interpretation.

Appendix E. Measurement Sensitivity

The measurement checks are supporting boundaries rather than alternative headline estimands. They proceed from direct input reconciliation and a simpler unemployment-only support check to alternative centers, vacancy pooling, published-error calibrations, and non-equivalent historical analogues. The sequence narrows the interpretation of the raw result without replacing it.

E.1. Input reconciliation and unemployment-only support

State-to-national reconciliation comes first. Table E1 compares labor-force-weighted state unemployment and vacancy inputs with their independently constructed national counterparts. The unemployment-only tables then repeat the exact accounting on a simpler observed state signal and compare named district rankings on identical support. This progression separates an input reconciliation check from a change in the primitive measurement object.

TABLE E1. State-to-National Input Reconciliation

Input	Months	Mean	Mean abs.	RMS	p10	Median	p90
Unemployment rate	299	0.000	0.071	0.092	-0.111	0.004	0.113
Job-openings rate	299	0.003	0.033	0.047	-0.044	-0.002	0.050

Note: Each row reports the monthly labor-force-weighted mean across 51 state/DC rates minus the independently constructed national rate, in percentage points, from January 2001 through December 2025 over 299 usable months. Unemployment and vacancy inputs are reconciled separately; the table does not apply the nonlinear UV benchmark or combine their differences. Quantiles use the standard type-7 sample convention. Exact equality is not imposed because the state and national official-statistics products are independently constructed.

TABLE E2. Unemployment-Only Squared-Distance Accounting

Window	Months	RMS unemployment percentage points			Share of total squared distance		
		Within	Between	Centering	Within	Between	Centering
Full available	299	0.830	0.733	0.092	55.8%	43.5%	0.7%
GFC recession	19	1.009	0.859	0.095	57.7%	41.8%	0.5%
ZLB recovery	78	1.061	0.992	0.103	53.1%	46.4%	0.5%
Post-ZLB/pre-COVID	48	0.521	0.363	0.076	66.3%	32.3%	1.4%
COVID shock	10	1.623	1.442	0.165	55.6%	43.9%	0.6%
Reopening/inflation	59	0.602	0.609	0.084	48.9%	50.1%	1.0%

Note: The table repeats Equation (1) using state unemployment rates as the primitive signal, the same fractional district allocator and monthly labor-force weights as the primary analysis, and the independently constructed national unemployment rate as the scalar. Every monthly and window identity reconciles below 10^{-10}. This is a simpler state-observed support check, not a county-level gap construction and not a substitute for the UV-gap estimand.

TABLE E3. District Rankings under Unemployment and the UV Gap

District	Unemp. mean abs.	Unemp. rank	UV mean abs.	UV rank	Rank diff.
Minneapolis	1.355	1	0.792	1	+0
Kansas City	1.000	2	0.670	2	+0
San Francisco	0.738	3	0.524	3	+0
Boston	0.596	4	0.394	7	-3
Dallas	0.577	5	0.474	4	+1
Atlanta	0.456	6	0.343	9	-3
Richmond	0.443	7	0.403	6	+1
New York	0.430	8	0.428	5	+3
Philadelphia	0.395	9	0.291	10	-1
Cleveland	0.372	10	0.271	11	-1
Chicago	0.339	11	0.381	8	+3
St. Louis	0.298	12	0.235	12	+0

Note: Districts are ranked by the unweighted mean across 299 months of the absolute district-minus-national residual; each district value is itself formed with the primary labor-force weighting. The UV comparison uses the primary raw district-minus-national UV-gap residual on identical support. A positive rank difference means the district ranks as less prominent under unemployment alone. Spearman rank correlation is 0.860. This ranking comparison is descriptive and does not replace the squared-distance accounting.

The unemployment-only exercise can validate the aggregation mechanics on a simpler signal, but it cannot substitute for the unemployment–vacancy gap or supply county-level vacancy evidence. The next cluster returns to the primary gap and keeps alternative centers and calibrations visibly separate.

E.2. Centering and core robustness

Table E4 defines the deterministic measurement lineages, and Table E5 reports their full- and matched-support results before they are condensed into the main robustness summary. Raw district distance, distance from the observed national input, matched-support distance, prior-window demeaning, and combined calibration answer different questions and therefore remain visibly separated.

TABLE E4. Specification Key for Measurement and Centering Lineages

Specification	Support	Center	Measurement change	Diagnostic question
Raw baseline	Full	Weighted district median	None (raw)	Raw common-scalar distance
Reliability sensitivity	Full	Weighted district median	Reliability calibration	Measurement reliability
Observed-national center	Full	Observed national input	Center only	Total national-input mismatch
Raw matched anchor	Matched	Weighted district median	Support only	Raw distance on matched support
History-adjusted sensitivity	Matched	Weighted district median	60-month prior demeaning	Persistent level differences
Combined sensitivity	Matched	Weighted district median	Reliability plus prior demeaning	Joint measurement sensitivity

Note: The key separates support, center, and measurement changes. Raw is the anchor within each support family; reliability, history adjustment, and combined variants are sensitivities, not corrections.

TABLE E5. Deterministic Measurement and Centering Results. Panel A: Full support

Window	Mo.	Level		Breadth				Recurrence	
		Mean absolute	RMS	Exposed share		Affected districts		Any month	
		Distance (gap pp)		25 bp	50 bp	25 bp	50 bp	25 bp	50 bp
Raw baseline Center: Weighted district median Change: None (raw) Question: Raw common-scalar distance									
Full available†	299	0.418	0.585	32.3%	8.5%	4.0	1.2	94.0%	37.8%
Ordinary pre-2020†	131	0.285	0.379	20.1%	0.3%	2.8	0.1	88.5%	6.9%
GFC recession	19	0.581	0.787	51.4%	20.8%	6.6	3.2	100.0%	84.2%
ZLB recovery	78	0.595	0.777	48.5%	20.0%	6.1	3.1	100.0%	92.3%
GFC/ZLB	97	0.592	0.779	49.1%	20.1%	6.2	3.1	100.0%	90.7%
COVID shock	10	0.877	1.117	62.1%	41.6%	7.4	4.4	100.0%	90.0%
Reopening / inflation†	59	0.357	0.451	27.5%	2.0%	2.7	0.2	98.3%	11.9%
Top-quartile pre-COVID	57	0.737	0.914	63.9%	28.7%	7.6	4.2	100.0%	100.0%
Reliability sensitivity Center: Weighted district median Change: Reliability calibration Question: Measurement reliability									
Full available†	299	0.353	0.512	24.2%	6.7%	2.9	1.0	79.6%	31.1%
Ordinary pre-2020†	131	0.211	0.279	8.4%	0.0%	1.1	0.0	60.3%	0.0%
GFC recession	19	0.513	0.704	46.2%	16.1%	6.1	2.5	100.0%	73.7%
ZLB recovery	78	0.532	0.698	44.4%	16.1%	5.5	2.5	100.0%	83.3%
GFC/ZLB	97	0.528	0.699	44.8%	16.1%	5.6	2.5	100.0%	81.4%
COVID shock	10	0.832	1.067	57.9%	34.6%	6.9	3.8	100.0%	90.0%
Reopening / inflation†	59	0.309	0.397	20.4%	1.4%	2.0	0.1	88.1%	8.5%
Top-quartile pre-COVID	57	0.672	0.834	61.7%	24.6%	7.4	3.7	100.0%	100.0%
Observed-national center **[Distinct diagnostic]** Center: Observed national input Change: Center only Question: Total national-input mismatch									
Full available†	299	0.433	0.569	33.0%	8.5%	3.8	1.1	94.0%	33.1%
Ordinary pre-2020†	131	0.298	0.367	19.2%	0.1%	2.5	0.0	88.5%	0.8%
GFC recession	19	0.609	0.724	55.3%	18.3%	6.4	2.2	100.0%	73.7%
ZLB recovery	78	0.616	0.759	51.1%	22.6%	6.0	3.0	100.0%	89.7%
GFC/ZLB	97	0.615	0.753	51.9%	21.7%	6.0	2.8	100.0%	86.6%
COVID shock	10	0.886	1.103	66.4%	36.9%	7.8	4.2	100.0%	90.0%
Reopening / inflation†	59	0.366	0.447	27.7%	1.0%	2.6	0.1	96.6%	8.5%
Top-quartile pre-COVID	57	0.753	0.884	65.1%	34.2%	7.4	4.1	100.0%	100.0%

Note: All rows describe district distances from a common input. Raw is the anchor within each support family, and the other lineages are sensitivities rather than successive corrections. The dagger marks the three windows whose raw month counts differ between full and matched support: Full available, Ordinary pre-2020, and Reopening inflation. The GFC recession, ZLB recovery, GFC/ZLB, COVID shock, and top-quartile pre-2020 windows have identical raw support across families. Full-support rows use up to 299 months; matched rows use identical strictly-prior eligible support of up to 237 months. The observed-national center diagnoses total national-input mismatch rather than common-scalar loss. Mean absolute and RMS distance are distinct level summaries. Thresholds use $\phi_x = 0.50$ and are illustrative rule-equivalent contributions, not realized rates or policy errors.

TABLE E5. Deterministic Measurement and Centering Results. Panel B: Matched support

Window	Mo.	Level		Breadth				Recurrence	
		Mean absolute	RMS	Exposed share		Affected districts		Any month	
		Distance (gap pp)		25 bp	50 bp	25 bp	50 bp	25 bp	50 bp
Raw matched anchor Center: Weighted district median Change: Support only Question: Raw distance on matched support									
Full available†	237	0.438	0.619	33.2%	10.5%	4.1	1.5	92.4%	43.9%
Ordinary pre-2020†	71	0.237	0.331	12.9%	0.0%	1.9	0.0	78.9%	0.0%
GFC recession	19	0.581	0.787	51.4%	20.8%	6.6	3.2	100.0%	84.2%
ZLB recovery	78	0.595	0.777	48.5%	20.0%	6.1	3.1	100.0%	92.3%
GFC/ZLB	97	0.592	0.779	49.1%	20.1%	6.2	3.1	100.0%	90.7%
COVID shock	10	0.877	1.117	62.1%	41.6%	7.4	4.4	100.0%	90.0%
Reopening / inflation†	57	0.357	0.451	27.7%	2.1%	2.7	0.2	98.2%	12.3%
Top-quartile pre-COVID	57	0.737	0.914	63.9%	28.7%	7.6	4.2	100.0%	100.0%
History-adjusted sensitivity Center: Weighted district median Change: 60-month prior demeaning Question: Persistent level differences									
Full available†	237	0.298	0.431	20.6%	3.6%	2.5	0.5	77.2%	24.5%
Ordinary pre-2020†	71	0.219	0.301	9.6%	0.7%	1.3	0.1	74.6%	8.5%
GFC recession	19	0.449	0.605	39.3%	11.9%	4.3	1.7	100.0%	89.5%
ZLB recovery	78	0.383	0.488	33.0%	3.4%	4.1	0.5	98.7%	32.1%
GFC/ZLB	97	0.396	0.513	34.3%	5.1%	4.2	0.7	99.0%	43.3%
COVID shock	10	0.706	0.928	55.5%	28.6%	6.1	3.2	100.0%	80.0%
Reopening / inflation†	57	0.165	0.242	5.8%	0.3%	0.6	0.0	40.4%	3.5%
Top-quartile pre-COVID	57	0.465	0.588	44.5%	7.8%	5.3	1.1	100.0%	63.2%
Combined sensitivity Center: Weighted district median Change: Reliability plus prior demeaning Question: Joint measurement sensitivity									
Full available†	237	0.269	0.399	17.7%	2.7%	2.2	0.4	69.2%	18.1%
Ordinary pre-2020†	71	0.183	0.261	6.3%	0.0%	1.0	0.0	54.9%	0.0%
GFC recession	19	0.411	0.558	35.7%	8.4%	3.9	1.3	100.0%	57.9%
ZLB recovery	78	0.351	0.446	29.2%	2.2%	3.8	0.3	98.7%	26.9%
GFC/ZLB	97	0.363	0.470	30.5%	3.4%	3.8	0.5	99.0%	33.0%
COVID shock	10	0.689	0.922	49.6%	28.5%	5.6	3.1	100.0%	90.0%
Reopening / inflation†	57	0.149	0.224	5.3%	0.3%	0.5	0.0	33.3%	3.5%
Top-quartile pre-COVID	57	0.422	0.537	41.2%	5.4%	4.8	0.9	100.0%	50.9%

Note: All rows describe district distances from a common input. Raw is the anchor within each support family, and the other lineages are sensitivities rather than successive corrections. The dagger marks the three windows whose raw month counts differ between full and matched support: Full available, Ordinary pre-2020, and Reopening inflation. The GFC recession, ZLB recovery, GFC/ZLB, COVID shock, and top-quartile pre-2020 windows have identical raw support across families. Full-support rows use up to 299 months; matched rows use identical strictly-prior eligible support of up to 237 months. The observed-national center diagnoses total national-input mismatch rather than common-scalar loss. Mean absolute and RMS distance are distinct level summaries. Thresholds use $\phi_x = 0.50$ and are illustrative rule-equivalent contributions, not realized rates or policy errors.

TABLE E6. Main Robustness Checks for the Lower Bound

Check	Main comparison	Lower-bound result
Full national vacancy pooling	Set every state vacancy rate equal to the national JOLTS rate before recomputing state and district gaps	0.34 gap pp in the full sample, 0.54 in the GFC/ZLB window, and 0.69 in pre-2020 top-spread months
Pre-2020 and ex-COVID timing	Remove post-2019 months or omit March–December 2020	0.42 gap pp before 2020, 0.40 after excluding the COVID shock window, and 0.73 in pre-2020 top-spread months
Split-state allocation	Replace county-population allocation with county-labor-force allocators; remove Connecticut split-state cells	Allocator ranges are below 0.01 gap pp; the Connecticut exclusion changes GFC/ZLB and top-spread lower bounds by less than 0.01 gap pp
Equal-district weighting	Give each district one-twelfth weight instead of labor-force exposure weights	0.41 gap pp in the full sample, 0.59 in the GFC/ZLB window, and 0.71 in top-spread months
Influence check	Remove exposed districts or state-district cells and renormalize the remaining district weights	Even the lowest listed exclusion estimates remain 0.38 gap pp in the full sample and 0.51 in the GFC/ZLB window

Note: Rows report the main robustness evidence used in the text. Full pooling uses the national-shrinkage row with $\lambda = 1$. Timing rows use the main sample-restriction checks. Split-state rows use the allocator sensitivity and Connecticut-exclusion checks. Equal-district rows recompute the weighted median with one-twelfth district weights. Influence rows report the lowest lower-bound values among the listed district and state-district-cell exclusions. Appendix tables report the full sets of windows, specifications, and construction details.

These tables show how the reported level changes when the center, support, weighting, or input construction changes. They do not turn the sensitivity lineages into corrected estimates. The next cluster states the additional assumptions required to interpret vacancy pooling and published-error calibrations.

E.3. Vacancy and measurement-error sensitivity

Write observed inputs as $\tilde{u}_{it} = u_{it} + \varepsilon^{u}_{it}$ and $\tilde{v}_{it} = v_{it} + \varepsilon^{v}_{it}$. For $u^* = \sqrt{uv}$, the delta-method approximation is

$$du^* = \frac{1}{2}\sqrt{\frac{v}{u}}\,du + \frac{1}{2}\sqrt{\frac{u}{v}}\,dv.$$

The reliability sensitivity uses state-specific recovered BLS spot-error anchors and assumes zero covariance between unemployment and vacancy errors, so the two derivative-scaled variances are added. It does not model cross-state or serial error covariance, revisions, or a complete historical state-month error process. The resulting reliability and combined lineages are assumption-dependent sensitivities, not corrected estimates.

Table E7 varies the pooling of State JOLTS vacancy inputs. The following two tables then compare published-error anchors with the variation required to explain the cross-state signal and carry that calibration into the common-input lower bound. This order distinguishes vacancy pooling from reliability shrinkage.

TABLE E7. Selected State JOLTS Shrinkage Results

Window	Months	Spread (bp)	National mismatch (bp)	Lower bound (bp)	Lower bound (gap pp)	Bound/spread
Raw state vacancy rates (λ = 0.00)						
Full sample	299	66.4	21.7	20.9	0.42	32%
Pre-2020	228	67.6	21.6	20.8	0.42	31%
GFC/ZLB	97	95.3	30.7	29.6	0.59	31%
Pre-2020 top-spread	57	118.1	37.6	36.7	0.73	31%
Census division shrinkage (λ = 0.50)						
Full sample	299	65.2	21.1	20.4	0.41	31%
Pre-2020	228	66.4	21.2	20.3	0.41	31%
GFC/ZLB	97	94.0	30.2	29.1	0.58	31%
Pre-2020 top-spread	57	116.8	37.2	36.4	0.73	31%
National shrinkage (λ = 0.50)						
Full sample	299	58.0	19.3	18.7	0.37	32%
Pre-2020	228	60.1	19.6	19.0	0.38	32%
GFC/ZLB	97	88.0	29.1	28.2	0.56	32%
Pre-2020 top-spread	57	110.2	36.2	35.4	0.71	32%
National shrinkage (λ = 1.00)						
Full sample	299	51.3	17.3	16.8	0.34	33%
Pre-2020	228	54.4	18.0	17.5	0.35	32%
GFC/ZLB	97	82.7	27.7	26.9	0.54	33%
Pre-2020 top-spread	57	106.1	35.1	34.4	0.69	32%

Note: Rows keep the baseline raw State JOLTS input, moderate Census-division pooling, moderate national pooling, and full national pooling. The omitted region-pooling, intermediate-lambda, smoothing, winsorization, and early-period-by-shrinkage rows are quantitatively similar and do not alter the lower-bound interpretation. Basis-point columns are rule-input basis points; gap pp divides by 50. National-input mismatch is weighted absolute district mismatch around the baseline national BLS/JOLTS input. Lower bound is the weighted absolute distance from the ex post weighted district median.

TABLE E8. Published-Error Anchors and Full-Noise Thresholds

Input channel	Critical statistic (pp)	BLS statistic (pp)	BLS/critical ratio	Weighted anchor tail share
LAUS unemployment rate	0.99	0.40	0.40	<0.001
State JOLTS job-openings rate	0.53	0.34	0.64	0.025

Note: Rows use the January 2001–December 2019 panel and ask how large the input-channel error statistic would need to be for classical measurement noise to explain all observed cross-state variation in state $u^* = \sqrt{uv}$. The BLS statistic is the labor-force-weighted root-mean-square published-error anchor from recovered LAUS seasonally adjusted unemployment-rate model-error tables and state-level State JOLTS job-openings-rate median-standard-error workbooks. The weighted anchor tail share is the labor-force-weighted share of available anchor observations at least as large as the critical statistic; it is a descriptive calibration quantity, not a hypothesis-test p-value. Input statistics are percentage points.

TABLE E9. Reliability Shrinkage and the Common-Input Lower Bound

Window	Months	Baseline (bp)	Published-error shrinkage (bp)	Change (bp)	Shrinkage / baseline
Pre-2020	228	20.8	17.3	-3.5	83.1%
GFC/ZLB	97	29.6	26.4	-3.2	89.1%
Pre-2020 top-spread	57	36.7	33.5	-3.2	91.4%

Note: Rows compare the baseline common-input lower bound with the delta-method reliability-shrinkage version based on the same recovered BLS published-error anchors. All lower-bound entries are rule-input basis points; dividing by 50 converts them to labor-market-gap percentage points under the baseline coefficient. The shrinkage exercise is a bounded calibration against spot published-error anchors, not a complete historical state-month measurement-error correction.

These are bounded attenuation exercises under stated assumptions. They do not recover a historical error process or warrant replacing the raw decomposition. The final cluster changes the signal or period more directly and is therefore kept as a separate interpretation boundary.

E.4. Historical analogues and period support

The county unemployment-history table is a non-equivalent local-measure analogue: it supplies long county histories but omits the vacancy input in the primary gap. The final period tables instead retain the baseline State JOLTS construction and vary the years included. Reading them together separates a change in measurement from a change in sample support.

TABLE E10. County Unemployment-History Analogue

Window	Baseline	History	Months	Spread	Bound
Full sample	20.9	10-year	299	71.7	22.2
Full sample	20.9	15-year	251	78.2	23.9
Pre-2020	20.8	10-year	228	73.9	23.0
Pre-2020	20.8	15-year	180	77.0	24.1
GFC/ZLB	29.6	10-year	97	79.3	24.9
GFC/ZLB	29.6	15-year	97	85.4	26.0
Full-sample top-spread	36.8	10-year	75	103.2	32.8
Full-sample top-spread	36.8	15-year	75	108.9	34.0
Pre-2020 top-spread	36.7	10-year	57	100.0	31.6
Pre-2020 top-spread	36.7	15-year	57	105.9	32.3

Note: All spread and lower-bound columns are rule-input basis points. Baseline repeats the state unemployment-vacancy lower bound from the main district results. County-history columns build district gaps directly from county LAUS unemployment rates and labor-force counts. The 10-year and 15-year gaps equal lagged trailing county unemployment means minus current county unemployment, aggregated to Federal Reserve districts with county labor-force weights. Connecticut old-county histories are reconstructed from town LAUS unemployment and labor-force series using the existing town-to-old-county crosswalk; Kalawao County has no usable county LAUS series and is omitted. Months are the nonmissing analysis months for each history window. Top-spread rows reuse the baseline exact district-spread selection rule within the stated sample: k = ceiling(0.25 N), with all months weakly above the kth-largest spread included.

TABLE E11. Period Sensitivity: Lower-Bound Levels

Period	Months	National-input mismatch (bp)	Lower bound (bp)	Lower bound (gap pp)	Centering loss (bp)	Bound / spread
2001-2004	48	18.2	17.6	0.35	0.6	33%
2001-2009	108	21.3	20.6	0.41	0.7	30%
2010-2019	120	21.9	21.0	0.42	0.9	32%
2001-2019	228	21.6	20.8	0.42	0.8	31%
2010-2025 excluding COVID	181	20.6	19.9	0.40	0.8	32%
Full sample	299	21.7	20.9	0.42	0.7	32%
Full sample excluding 2001-2009	191	21.9	21.1	0.42	0.7	32%
Full sample excluding 2001-2004	251	22.3	21.6	0.43	0.8	31%

Note: Rows average monthly baseline raw State JOLTS outputs over the listed period. The 2010–2025 excluding COVID row removes March–December 2020; full-sample exclusion rows remove the listed early years from the 2001–2025 panel. National-input mismatch and lower bound are rule-input basis points; gap pp divides lower bound bp by 50. Bound/spread divides the period-average lower bound by the period-average district spread.

TABLE E12. Period Sensitivity: Aggregation Diagnostics

Period	Months	State spread (bp)	District spread (bp)	District/state spread ratio
2001-2004	48	78.2	52.9	68%
2001-2009	108	94.1	68.7	73%
2010-2019	120	103.3	66.6	65%
2001-2019	228	98.9	67.6	68%
2010-2025 excluding COVID	181	95.1	61.5	65%
Full sample	299	97.9	66.4	68%
Full sample excluding 2001-2009	191	100.1	65.1	65%
Full sample excluding 2001-2004	251	101.7	69.0	68%

Note: Rows average monthly baseline raw State JOLTS outputs over the listed period. The 2010–2025 excluding COVID row removes March–December 2020; full-sample exclusion rows remove the listed early years from the 2001–2025 panel. State and district spreads are weighted p90-p10 spreads in rule-input basis points. District/state spread ratio divides the period-average district spread by the period-average state spread.

Together, these checks bound rather than replace the raw state unemployment–vacancy accounting.