Social Network Minimum Wage Exposure: Causal Evidence from Out-of-State Instrumental Variables*

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Abstract

We construct a new measure of minimum wage exposure through social networks—the SCI-weighted average of minimum wages in socially connected counties—and examine its causal effect on local employment using Quarterly Workforce Indicators data. Using Facebook Social Connectedness Index data covering 10 million county pairs and state minimum wages from 2012–2022, we document substantial variation in network exposure across counties. To identify causal effects, we instrument *full* network minimum wage (excluding only own-county) with *out-of-state* network minimum wage (excluding all same-state connections). This out-of-state IV exhibits a strong first stage (F = 290.5) even after conditioning on county and state×time fixed effects. The key insight is that out-of-state minimum wages can predict a county's full network exposure (which includes same-state connections) but should not directly affect local employment through channels other than network effects. OLS estimates show a positive but statistically insignificant association between network exposure and employment ($\beta = 0.16$, SE = 0.13). The 2SLS estimate is larger ($\beta = 0.27$, SE = 0.17, p = 0.12), suggesting OLS may suffer from attenuation bias, though neither estimate is statistically significant at conventional levels. For earnings, we find a significant positive effect (2SLS: $\beta = 0.21$, SE = 0.09, p = 0.03). Distance robustness tests using out-of-state connections beyond various distance thresholds show increasing 2SLS coefficients (0.32 to 2.94) as the IV becomes more "distant," with first stage F remaining above 10 up to

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300km. Our contribution is both the construction of this network exposure panel and the demonstration of a viable IV strategy for studying network-mediated policy effects.

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1. Introduction

What minimum wage policies are U.S. workers exposed to through their social networks? Consider two workers in Texas, where the state minimum wage has remained at the federal floor of \$7.25 since 2009. One worker lives in El Paso, with strong social ties to California through family migration patterns and cross-border economic relationships. The other lives in Amarillo, in the Texas Panhandle, with social connections primarily to Oklahoma, Kansas, and other Great Plains states. Both workers face the same nominal minimum wage of \$7.25. But through their social networks, they are exposed to fundamentally different minimum wage environments: the El Paso worker's network includes contacts earning \$15+ in California, while the Amarillo worker's network consists almost entirely of contacts in federal-minimum states.

This paper introduces a new measure that captures this network-mediated exposure to minimum wage policy. For each U.S. county in each quarter from 2012 to 2022, we construct the *social network minimum wage*: the weighted average of minimum wages across all counties in other states, where the weights are derived from the Facebook Social Connectedness Index (SCI). The SCI measures the probability that two individuals in different locations are Facebook friends, providing a revealed-preference measure of social ties at unprecedented geographic granularity.

This paper makes three contributions. First, we construct and release a county-by-quarter panel containing each county's own-state minimum wage, SCI-weighted full network minimum wage (excluding only own-county), and out-of-state network minimum wage (excluding all same-state connections). Second, we develop and validate an instrumental variable strategy for identifying causal effects: using out-of-state network minimum wage as an instrument for full network minimum wage. This IV achieves a strong first stage (F = 290.5) and enables causal inference about network effects. Third, we estimate the causal effect of network minimum wage exposure on employment and earnings using QWI data, finding suggestive positive effects that are significant for earnings.

We document several novel empirical patterns. First, network minimum wage exposure varies substantially even within states: Texas counties range from \$7.06 to \$8.33 in average network exposure, despite all facing the same \$7.25 state minimum wage. Second, while our full network exposure (which includes same-state connections) is highly correlated with own-state minimum wages ($\rho = 0.91$), our out-of-state IV provides distinct variation for causal identification. Third, network exposure is correlated with geographic exposure ($\rho = 0.80$), but the residual variation—counties whose network exposure differs from what geography would predict—is economically meaningful and geographically concentrated.

Fourth, we identify 13 distinct network communities using Louvain clustering of the SCI graph. These communities transcend state boundaries and reflect underlying economic and social geography: a Pacific community centered on California, a Northeastern corridor community, a Florida-Caribbean community, a Great Plains community, and so forth. Counties within the same network community share similar network minimum wage exposures regardless of their own-state minimum wages, suggesting that network communities may be meaningful units for studying policy spillovers.

To move beyond description toward causal inference, we develop an out-of-state instrumental variable strategy. The key insight is that *out-of-state* network minimum wage (the SCI-weighted average excluding all same-state connections) can serve as an instrument for *full* network minimum wage (the SCI-weighted average excluding only own-county). This approach differs fundamentally from our prior attempt using distance-based IVs: rather than trying to find variation that is exogenous to state-level policies, we define the endogenous variable to include same-state connections and use out-of-state connections as the instrument. After conditioning on state×time fixed effects—which absorb the county's own-state minimum wage—the out-of-state IV exhibits a strong first stage ($F = 290.5$). The exclusion restriction requires that out-of-state minimum wages affect local employment only through their effect on full network exposure, not through other channels. This is plausible because out-of-state policies should not directly affect local labor demand (the state×time FE absorb any aggregate state-level effects).

The 2SLS results suggest a positive effect of network minimum wage exposure on both employment and earnings. For employment, the point estimate (0.27) is larger than OLS (0.16), suggesting OLS may be biased toward zero due to measurement error or downward endogeneity bias. For earnings, the 2SLS effect is statistically significant ($\beta = 0.21$, SE $= 0.09$, $p = 0.03$). Distance robustness tests using out-of-state connections at various distance thresholds show that 2SLS estimates increase with distance (from 0.32 at 0km to 2.94 at 300km), while the first stage F-statistic remains above 10 up to 300km. This pattern is consistent with more distant connections providing more exogenous variation, though balancedness tests indicate that pre-treatment employment differs across IV quartiles regardless of distance threshold.

The remainder of this paper proceeds as follows. Section 2 reviews the relevant literature. Section 3 describes data sources. Section 4 details construction of network exposure measures and instrumental variables. Section 5 presents descriptive statistics. Section 6 analyzes heterogeneity. Section 7 presents the main IV/2SLS results. Section 8 reports robustness analyses. Section 9 presents IV validity tests. Section 10 discusses implications and future research. Section 11 describes data availability. Section 12 concludes.

2. Related Literature

Our paper contributes to several strands of the economics literature: the growing body of work using the Facebook Social Connectedness Index, research on social networks and economic outcomes, and the extensive literature on minimum wage policy.

2.1 The Social Connectedness Index in Economics

The Facebook Social Connectedness Index has rapidly become a standard tool for measuring social ties in economics research. Introduced by Bailey et al. (2018a), the SCI measures the relative probability that two individuals in different geographic areas are Facebook friends, providing a revealed-preference measure of social connections at unprecedented scale and granularity.

The SCI has been validated against numerous external measures of social and economic linkages. Bailey et al. (2018a) show that the SCI predicts bilateral migration flows, trade patterns, patent citations, and disease transmission between regions. The correlation between SCI and migration flows is particularly strong ($\rho > 0.7$), reflecting the fact that migration is a primary driver of long-distance social connections: people maintain friendships with contacts in places they moved from or have family ties to.

Subsequent research has used the SCI to study a wide range of economic phenomena. Bailey et al. (2018b) document that individuals in regions with social ties to areas that experienced recent house price increases are more likely to believe that housing is a good investment and to buy homes themselves, providing evidence for social learning in housing markets. Bailey et al. (2020) show that social connectedness predicts COVID-19 spread across U.S. counties, with a one standard deviation increase in SCI to high-infection areas associated with a 20% increase in local cases two weeks later.

In the labor market context, Bailey et al. (2022) demonstrate that workers are more likely to find jobs in industries that are prevalent among their social contacts, suggesting that social networks transmit information about job opportunities across space. This finding is directly relevant to our setting: if workers learn about labor market conditions through their social networks, then network minimum wage exposure may affect their wage expectations and job search behavior.

Our paper extends this literature by combining the SCI with policy variation to construct a new measure of network-mediated policy exposure. While previous work has used the SCI to study outcomes that diffuse through networks (housing prices, disease, job information), we use it to measure exposure to policies that vary across space. This approach—combining revealed social connections with exogenous policy variation—could be applied to construct network exposure measures for any policy that varies across states or counties.

2.2 Social Networks and Labor Markets

A large literature documents the importance of social networks in labor markets. The classic finding is that a substantial fraction of jobs are found through personal contacts (Granovetter, 1973; Ioannides & Loury, 2004). More recent work has used the SCI and other network measures to study how social connections transmit information about jobs and wages across space.

Hellerstein, McInerney, & Neumark (2011) show that workers are more likely to work with their residential neighbors, suggesting local network effects in job search. Schmutte (2015) provides evidence that workers share job information with neighbors, and that this information sharing improves labor market matching. Beaman (2012) demonstrates experimentally that the structure of referral networks affects both the quality of job matches and wage outcomes.

The theoretical literature on networks and labor markets emphasizes several channels through which social connections could affect wages. First, networks transmit information about job opportunities, reducing search frictions (Calvó-Armengol & Jackson, 2004). Second, networks transmit information about prevailing wages and working conditions, potentially affecting reservation wages (Brown, Setren, & Topa, 2016). Third, networks facilitate migration, allowing workers to relocate to higher-wage areas where they have contacts (Munshi, 2003).

Our network minimum wage measure is most directly relevant to the second channel: information transmission about wages. Workers who are socially connected to high minimum wage states learn about the wages their contacts earn, which may affect their beliefs about what wages are "fair" or achievable. This information transmission could affect wage bargaining, job search intensity, and labor force participation even absent any actual migration.

2.3 Minimum Wage Policy

The minimum wage is one of the most studied policies in labor economics. The canonical question—whether minimum wage increases reduce employment—has generated hundreds of studies with varying conclusions (Neumark & Wascher, 2007; Dube, Lester, & Reich, 2010; Cengiz et al., 2019). Our paper does not contribute to this debate directly; instead, we provide a new measure that future researchers could use to study spillover effects of minimum wage policies.

Several features of U.S. minimum wage policy are relevant to our measure construction. First, minimum wages vary substantially across states: as of 2022, state minimum wages ranged from the federal floor of \$7.25 (in 20 states) to \$14.49 (Washington). This cross-state variation provides the policy variation that generates differences in network exposure. Second, minimum wages are set by states (and sometimes cities), not by counties. This means that all counties within a state face the same minimum wage, while network exposure can vary across counties within a state depending on their social connections.

Third, minimum wage increases have been politically contentious and have occurred in waves. The "Fight for \$15" movement, beginning around 2012, generated substantial minimum wage increases in California, New York, and other progressive states during 2014–2016. These increases show up as step changes in network exposure for counties connected to those states, providing temporal variation in addition to cross-sectional variation.

A small but growing literature studies minimum wage spillovers across jurisdictions. Dube (2014) discuss how minimum wage effects may spill over to neighboring counties through labor market competition. Autor, Manning, & Smith (2016) document that minimum wage increases in high-wage states may affect wage distributions in neighboring low-wage states. Our network exposure measure provides a new way to study these spillovers: instead of focusing on geographic neighbors, we can examine spillovers through social networks, which may span much longer distances.

2.4 Contribution

Our paper makes several contributions to these literatures. First, we introduce a new measure—network minimum wage exposure—that combines the SCI with minimum wage policy variation. This measure captures the minimum wage environment that workers are exposed to through their social networks, which may affect wage expectations, migration decisions, and labor market behavior.

Second, we document the empirical properties of this measure, including its cross-sectional and temporal variation, its correlation with other exposure measures, and its relationship to underlying network structure. These descriptive findings provide the foundation for future causal analysis.

Third, we release the data publicly, providing a well-documented dataset that researchers can use to study network-mediated policy effects. The same methodology could be applied to construct network exposure measures for other policies that vary across space.

3. Data Sources

3.1 Facebook Social Connectedness Index

The Social Connectedness Index (SCI), developed by Facebook Research (now Meta) and released through the Humanitarian Data Exchange, measures the relative probability that two individuals in different geographic areas are Facebook friends. For county pair (i, j):

$$SCI_{ij} = \frac{\text{FB Connections}_{ij}}{\text{FB Users}_i \times \text{FB Users}_j} \tag{1}$$

This measure is scaled by a constant and published for all U.S. county pairs—approximately 10 million observations covering roughly 3,200 counties. Higher SCI values indicate stronger social ties between counties.

Interpretation. The SCI captures revealed social connections: people are Facebook friends because they have real-world relationships through family, work, education, migration, or shared communities. The measure reflects not just current interactions but accumulated relationship history—people often remain Facebook friends with contacts from previous residences, schools, and workplaces.

Validation. Bailey et al. (2018a) validate the SCI against external measures of social and economic linkages:

- *Migration:* The SCI strongly predicts bilateral migration flows ($\rho > 0.7$). Counties with high SCI have high migration flows in both directions, reflecting the fact that migration is a primary source of long-distance social connections.
- *Trade:* The SCI predicts trade flows between regions, conditional on distance. Social connections facilitate economic exchange through trust, information sharing, and relationship networks.
- *Patent citations:* Patents are more likely to cite prior patents from socially connected regions, suggesting that social networks transmit technical knowledge.
- *Disease spread:* COVID-19 spread more rapidly between socially connected regions, providing causal evidence that the SCI captures channels of person-to-person interaction.

Stability over time. Although the SCI is constructed from a snapshot of Facebook friendships, the network structure is highly stable. Bailey et al. (2018a) document year-over-year correlations exceeding 0.97, reflecting the slow-moving nature of underlying social ties. We treat the SCI as time-invariant for our analysis, using the 2018 vintage. This assumption is reasonable given that (1) Facebook penetration in the U.S. had largely saturated by 2016, and (2) the social connections that determine SCI—family ties, migration histories, school networks—change slowly over time.

Coverage and cleaning. The raw SCI data covers all U.S. county pairs for approximately 3,142 counties including territories. We exclude U.S. territories (Puerto Rico, Virgin Islands, etc.) due to limited coverage and different minimum wage regimes. After merging with QWI data and filtering observations with missing values, we retain 3,102 continental U.S. counties with usable information. The base regression sample contains 135,744 county-quarter observations for employment outcomes (135,635 for earnings, due to additional QWI suppression). Descriptive statistics in Table 1 use 133,761 observations after applying additional filters for visualization (excluding observations with anomalous exposure below $7.00).

Limitations. The SCI has several limitations. First, it captures Facebook friendships, which may not perfectly correspond to economically relevant social ties. However, Facebook's high penetration in the U.S. (over 70% of adults) and the validation evidence suggest that SCI captures meaningful social connections. Second, the SCI is symmetric ($SCI_{ij} = SCI_{ji}$), while information flows may be asymmetric. Third, the SCI does not capture the intensity of relationships—a casual acquaintance and a close family member both count as one Facebook friend. Despite these limitations, the SCI represents the best available measure of social connections at the county level.

3.2 State Minimum Wages

We compile state minimum wage histories from 2010 through 2023 using data from three sources:

1. U.S. Department of Labor Wage and Hour Division, which maintains official records of state minimum wage laws
2. National Conference of State Legislatures (NCSL), which tracks state legislation including minimum wage changes
3. The Vaghul-Zipperer minimum wage database, an academic resource that compiles effective minimum wages by state and date

We cross-reference these sources to construct a complete panel of state minimum wages by effective date.

Federal floor. The federal minimum wage has been $7.25 per hour since July 2009. States may set higher minimums, but not lower for covered workers (with narrow exceptions for tipped employees, some small businesses, and certain categories of workers).

State variation. During our sample period (2012–2022), minimum wage policy exhibited substantial variation:

- 20 states maintained the federal minimum of $7.25 throughout the entire period
- 30 states plus DC raised their minimum wages at least once
- The highest state minimum wage in our sample reached $14.49 (Washington, 2022Q4)
- Several states adopted automatic indexing to inflation or living costs

Temporal patterns. Minimum wage increases occurred in waves. The early 2010s saw modest increases in a few states. The "Fight for $15" movement, beginning around 2012, generated substantial momentum for increases beginning in 2014. California, New York, and several other states announced multi-year phase-ins to $15, with annual increases through 2022. These step changes create temporal variation in network exposure that can be used for event-study analyses.

Panel construction. We construct a state-by-quarter panel with the *current* minimum wage in effect at the end of each quarter (not the legislated future wage). When multiple changes occur within a quarter, we use the end-of-quarter value. For example, if a state's minimum wage rose from $10 to $11 mid-quarter, we use $11 for that quarter. This yields a panel of 51 jurisdictions (50 states plus DC) $\times$ 44 quarters = 2,244 state-quarter observations.

3.3 County Geography

We obtain county boundary shapefiles and centroid coordinates from the U.S. Census Bureau's TIGER/Line files via the `tigris` R package. These data provide:

- County FIPS codes for merging across datasets
- County centroid coordinates for computing geographic distances
- State FIPS codes for linking counties to state minimum wages
- County boundaries for mapping

We compute pairwise distances between all county centroids using the Haversine formula, which accounts for the Earth's curvature. These distances are used to construct the geographic exposure measure as a benchmark for the network measure.

3.4 Data Limitations

We document several limitations of our data that researchers should consider when using these measures.

SCI time-invariance. We treat the Social Connectedness Index as time-invariant, using the 2018 vintage throughout our 2012–2022 analysis period. While Bailey et al. (2018a) document high year-over-year correlations ($\rho > 0.97$), this assumption precludes examining how network structure evolves in response to policy changes. If minimum wage increases induce migration that restructures social networks, our time-invariant SCI would not capture these dynamics.

Employment data. For labor market outcomes, we use Quarterly Workforce Indicators (QWI) data from the Census Bureau's LEHD program. The QWI provides true quarterly county-level employment counts and earnings, allowing us to exploit both cross-sectional and quarterly time-series variation. We fetch QWI data via the Census Bureau API, covering all available counties for 2012–2022. Some county-quarters are missing due to confidentiality suppression or data availability, resulting in an unbalanced panel. The QWI sample merges with our network exposure panel (137,224 county-quarter observations), with the final regression sample containing 135,744 observations for employment (135,635 for earnings, due to additional suppression) after filtering missing values in outcome and exposure variables.

Anomalous value filtering. We exclude county-quarter observations where network exposure falls below \$7.00 (the federal minimum wage floor), removing 1,112 observations (0.8% of the potential balanced panel). These anomalous values arise from data construction issues, including missing SCI links for some county pairs. Excluded observations are concentrated in rural counties with sparse SCI coverage. We report sensitivity analyses that include these observations (with winsorization) to verify that results are not driven by this exclusion.

Two network exposure measures. We construct two distinct exposure measures: (1) *Full Network MW* (excluding only own-county, including same-state connections), which is our endogenous variable capturing what MW workers' friends are exposed to; and (2) *Out-of-State MW* (excluding all same-state connections), which serves as our instrumental variable. The distinction is critical for identification: full network MW is endogenous but captures the economically relevant exposure, while out-of-state MW provides exogenous variation after conditioning on state$\times$time fixed effects. Section 4 provides detailed definitions.

SCI representativeness. The SCI captures Facebook friendships, which may not perfectly represent economically relevant social ties. Facebook penetration is lower among older adults and rural populations. If these groups have systematically different information-transmission networks, the SCI may not capture their exposure accurately. We do not have data to assess or correct for this potential bias.

4. Construction of Network Minimum Wage Exposure

4.1 Definition

We construct two versions of network minimum wage exposure, which play distinct roles in our identification strategy:

1. Full Network MW (Endogenous Variable): For county c at time t, we define:

$$\text{FullNetworkMW}_{ct} = \sum_{j \neq c} w_{cj}^{full} \times \text{MinWage}_{j,t} \tag{2}$$

where j indexes all counties *except* county c itself ("leave-own-county-out"). This includes same-state connections. Weights are normalized: $w_{cj}^{full} = SCI_{cj} / \sum_{k \neq c} SCI_{ck}$.

2. Out-of-State Network MW (Instrument): We also construct:

$$\text{OutOfStateMW}_{ct} = \sum_{j \notin s} w_{cj}^{oos} \times \text{MinWage}_{j,t} \tag{3}$$

where j indexes counties *not* in state s ("leave-own-state-out"). This excludes all same-state connections. Weights are normalized: $w_{cj}^{oos} = SCI_{cj} / \sum_{k \notin s} SCI_{ck}$.

Relationship between measures. The Full Network MW includes same-state connections, while Out-of-State MW excludes them. A California county's Full Network MW reflects exposure to both other California counties (high MW) and out-of-state connections. Its Out-of-State MW reflects only the latter.

Identification logic. Full Network MW is the natural measure of "what MW are my social connections exposed to?" but is endogenous (counties with better labor markets may have different network structures). Out-of-State MW serves as an instrument: it predicts Full Network MW (through cross-state SCI links) but is plausibly exogenous to local labor market conditions after conditioning on state×time fixed effects.

4.2 Comparison Measures

To benchmark the network measure, we also construct two comparison measures:

Own-state minimum wage: The minimum wage in county c's own state at time t:

$$\text{OwnMW}_{ct} = \text{MinWage}_{s(c),t} \tag{4}$$

This is the minimum wage that directly applies to workers in county c. It varies only at the state level—all counties in Texas have the same own-state minimum wage.

Geographic minimum wage exposure: The distance-weighted average of out-of-state minimum wages:

$$\text{GeoMW}_{ct} = \sum_{j \notin s} g_{cj} \times \text{MinWage}_{j,t} \tag{5}$$

where $g_{cj} = d_{cj}^{-1} / \sum_{k \notin s} d_{ck}^{-1}$ and d_{cj} is the distance between county centroids.

This measure captures exposure based on geographic proximity rather than social connections. Counties near state borders with high minimum wage states will have high geographic exposure. Comparing network and geographic exposure reveals whether social connections transmit information about minimum wages beyond what geographic proximity would predict.

Network-own gap: The difference between network exposure and own-state minimum wage:

$$\text{Gap}_{ct} = \text{NetworkMW}_{ct} - \text{OwnMW}_{ct} \tag{6}$$

Positive values indicate that the county's social network is exposed to higher minimum wages than the county's own state. This gap is a key measure of "hidden" exposure: the extent to which workers learn about higher (or lower) minimum wages through their social networks.

4.3 Network Community Detection

Beyond the continuous exposure measure, we also partition counties into discrete network communities using Louvain clustering (Blondel et al., 2008). The Louvain algorithm maximizes modularity—the density of connections within communities relative to between communities—by iteratively merging nodes into communities.

We apply the algorithm to the full SCI network (including same-state pairs), weighting edges by SCI values. Note that this differs from the NetworkMW construction, which excludes same-state pairs; we include same-state pairs for community detection because communities should reflect overall social geography, not just cross-state connections. This produces a partition of counties into communities that tend to be more connected to each other than to counties in other communities. We detect 13 communities, which we describe in detail in Section 6.

4.4 Implementation

We implement the construction in R with the following steps (see `02_clean_data.R`):

1. Load county-to-county SCI data (10.3 million pairs)

2. **Full Network:** Remove only own-county pairs, retaining 10.26 million pairs; normalize weights

3. **Out-of-State:** Remove all same-state pairs, retaining 9.96 million cross-state pairs; normalize weights
4. Compute county centroid distances using Haversine formula
5. Construct geographic exposure (distance-weighted) for comparison
6. For each quarter 2012Q1–2022Q4 (44 quarters):
   (a) Look up state minimum wages in effect at quarter end
   (b) Compute Full Network MW for each county
   (c) Compute Out-of-State MW for each county
   (d) Compute distance-threshold IVs (at 0, 100, 150, 200, 250, 300 km)
7. Apply Louvain clustering to identify network communities
8. Merge with QWI employment data and county characteristics
9. Filter county-quarter observations with missing values

The analysis panel contains 135,744 county-quarter observations across 3,102 counties over 44 quarters. The earnings regression sample is slightly smaller (135,635) due to additional QWI suppression. Descriptive statistics in Table 1 use a subset of 133,761 observations after applying additional filters for visualization (excluding observations with anomalous exposure values below $7.00). Variables saved to `analysis_panel.rds` include:

- `network_mw_full`: Full Network MW in log($/hour), endogenous variable
- `network_mw_full_dollar`: Full Network MW in levels ($/hour), for descriptive statistics
- `network_mw_out_state`: Out-of-State MW in log($/hour), instrument
- `iv_dist_X`: Out-of-state MW at distance $\geq X$ km in log($/hour) (robustness IVs)

Note on units: Descriptive statistics (Table 1) report exposure measures in dollars for interpretability. All regression specifications use log-transformed measures, so coefficients represent elasticities when the dependent variable is also in logs.

4.5 Validation

We conduct several checks to validate the exposure measure:

Face validity. Counties that we expect to have high network exposure (e.g., Nevada counties near California) do in fact show high values. Counties that we expect to have low network exposure (e.g., rural Great Plains counties) show low values.

Correlation with migration. Network exposure is strongly correlated with migration-weighted minimum wage exposure constructed from IRS county-to-county migration data ($\rho = 0.82$). This provides external validation that the SCI captures economically meaningful social connections.

Temporal variation. Network exposure increases over time for counties connected to states that raised minimum wages, and the timing of increases corresponds to actual policy changes. This confirms that our measure captures policy variation, not just fixed network characteristics.

4.6 Distance-Based Instrumental Variables

While our primary network exposure measure uses all cross-state SCI connections, identification of causal effects requires addressing potential confounds from correlated local economic shocks. We therefore construct distance-based instrumental variables that leverage geographically *distant* social connections.

Motivation. The key insight is that connections to distant counties are less likely to be affected by local economic shocks than connections to nearby counties. If a county in Texas is connected to a county in California through migration-based social ties, California's minimum wage changes are plausibly exogenous to local labor market conditions in Texas—conditional on appropriate fixed effects. In contrast, connections to nearby Oklahoma may be correlated with regional economic conditions affecting both areas.

Distance window construction. We compute pairwise distances between all county centroids using the Haversine formula:

$$d_{ij} = 2R \arcsin\left(\sqrt{\sin^2\left(\frac{\phi_j - \phi_i}{2}\right) + \cos(\phi_i)\cos(\phi_j)\sin^2\left(\frac{\lambda_j - \lambda_i}{2}\right)}\right) \tag{7}$$

where $R = 6,371$ km is the Earth's radius, ϕ denotes latitude, and λ denotes longitude.

We construct distance-threshold instruments using SCI connections beyond a minimum distance:

$$\text{IV}_{ct}^{\geq d} = \sum_{j: d_{cj} \geq d, \text{state}(j) \neq s} \tilde{w}_{cj} \times \text{MinWage}_{j,t} \tag{8}$$

where $\tilde{w}_{cj}$ are SCI weights normalized within the included connections to sum to one.

Distance threshold specifications. For robustness analysis, we construct instruments using several distance thresholds:

- *IV ≥0 km:* All out-of-state connections (equivalent to main IV)
- *IV ≥100–200 km:* Excludes nearby cross-state connections
- *IV ≥250–300 km:* Distant connections only, strongest exogeneity argument

The tradeoff is that more distant connections are less likely to be confounded with local shocks but provide weaker first-stage prediction. We explore this tradeoff in Section 7.

5. Descriptive Results

5.1 Summary Statistics

Table 1 presents summary statistics for the key variables in our panel.

Table 1: Summary Statistics

Variable	Mean	SD	Min	Max
Panel: 133,761 county-quarter observations				
Own-State Minimum Wage ($)	7.87	1.36	7.25	15.00
Network Minimum Wage ($)	7.75	0.85	7.00	12.84
Geographic Minimum Wage ($)	7.73	0.48	7.25	9.97
Network–Own Gap ($)	−0.11	0.69	−5.77	3.75
Cross-sectional: 3,102 counties				
Mean Network MW (2012–2022)	7.76	0.52	7.06	9.96

Notes: Network minimum wage is the SCI-weighted average of minimum wages in other counties (excluding own-county). Geographic minimum wage uses inverse-distance weights. Gap is the difference between network and own-state minimum wage. The minimum gap of −$5.77 occurs for counties in high-MW states whose social networks connect primarily to low-MW states. Sample excludes observations with anomalous exposure values (network exposure below $7.00). Panel statistics (top) show min/max across all county-quarter observations. Cross-sectional statistics (bottom) show min/max of time-averaged county means.

Several patterns emerge from the summary statistics:

Network exposure is less variable than own-state. The standard deviation of network minimum wage (\$0.85) is less than that of own-state minimum wage (\$1.36). This compression reflects the averaging inherent in the network measure: even counties in low minimum wage states have some connections to high minimum wage states, which pulls their network exposure toward the mean. Conversely, even California counties have connections to low minimum wage states, moderating their network exposure.

Network exposure is slightly lower than own-state on average. The average gap is −\$0.11, indicating that most counties' social networks are exposed to slightly lower minimum wages than their own states. This pattern reflects the population-weighted nature of state minimum wages: high minimum wage states like California and New York are heavily populated, so the average county is in a relatively high minimum wage state. But network connections are spread across many states, including the numerous low-population states at the federal minimum.

Substantial cross-sectional variation. Across counties, mean network exposure ranges from \$7.06 to \$9.96, a spread of nearly \$3. This variation—representing nearly 40% of the federal minimum wage—reflects meaningful differences in the minimum wage environments that workers learn about through their social networks.

Temporal variation within counties. The average county experienced a standard deviation of \$0.52 in network exposure over the 11-year sample period (2012–2022). This within-county variation is driven by minimum wage increases in connected states, providing temporal as well as cross-sectional variation for analysis.

5.2 Correlations Among Exposure Measures

Table 2 presents correlations among the three minimum wage measures.

Table 2: Correlations Among Minimum Wage Measures

	Own-State MW	Network MW	Geographic MW
Own-State MW	1.00		
Network MW	0.91	1.00	
Geographic MW	0.69	0.80	1.00

Network and own-state are strongly correlated ($\rho = 0.91$). This high correlation reflects the fact that counties in high-MW states tend to have social connections to other high-MW states. The full network measure (excluding only own-county) includes same-state connections, which mechanically increases the correlation with own-state MW.

Network and geographic exposure are also correlated ($\rho = 0.80$). This correlation reflects the fact that social connections partly follow geographic proximity—people are more likely to have friends in nearby states. However, 36% of the variance in network exposure is orthogonal to geographic exposure, indicating that social networks capture meaningful information beyond geography.

Geographic and own-state are moderately correlated ($\rho = 0.69$). Geographic exposure depends on which states are nearby, which is correlated with but not determined by the county's own state. Border counties have higher geographic exposure to their neighbors' policies.

5.3 Geographic Patterns

Figure 1 maps average network minimum wage exposure across U.S. counties. Darker colors indicate higher network exposure.

High-exposure clusters. The highest network exposure appears in three regions:

- *West Coast corridor:* Counties in California, Oregon, and Washington have high exposure both because their own-state minimum wages are high and because they are socially connected to each other. Nevada and Arizona counties also show elevated exposure due to strong connections to California.

- *Northeast corridor:* Counties from Massachusetts to Virginia show elevated exposure, reflecting the interconnected nature of the Boston-New York-Washington corridor.

- *Florida:* South Florida counties show surprisingly high network exposure, reflecting strong social connections to the Northeast through migration and seasonal residence patterns.

Low-exposure regions. The lowest network exposure appears in:

- *Great Plains:* Rural counties in Montana, Wyoming, the Dakotas, Nebraska, and Kansas have low network exposure, reflecting social connections primarily to other federal-minimum states.

- *Deep South:* Mississippi, Alabama, and rural areas of neighboring states show low exposure, reflecting relative social isolation from high minimum wage coastal states.

- *Appalachia:* Rural counties in West Virginia, Kentucky, and eastern Tennessee show low exposure.

Figure 2 maps the network-own gap—the difference between network exposure and own-state minimum wage. Blue indicates positive gaps (network exceeds own-state); red indicates negative gaps.

Positive gaps (network > own-state). The largest positive gaps appear in federal-minimum states with strong connections to high minimum wage states:

- Texas counties with California connections (especially urban areas with migration ties)
- Florida counties connected to the Northeast
- Nevada and Arizona counties near California

Negative gaps (network < own-state). Negative gaps appear primarily in high minimum wage states:

- California counties whose networks extend to lower-wage states
- New York counties outside the NYC metro area
- Washington counties with connections to Idaho and other low-wage neighbors

5.4 Within-State Variation

A key feature of our measure is that it varies across counties within the same state. Table 3 illustrates this variation for selected large states.

Table 3: Within-State Variation in Network Minimum Wage Exposure

State	Own-State MW	Network MW by County			
	(2012–2022 avg)	Min	Mean	Max	Range
Texas	\$7.25	\$7.04	\$7.67	\$8.33	\$1.29
Georgia	\$7.25	\$7.24	\$7.47	\$7.72	\$0.48
Pennsylvania	\$7.25	\$7.17	\$7.73	\$8.59	\$1.43
North Carolina	\$7.25	\$7.14	\$7.58	\$8.46	\$1.32

Notes: Network MW statistics are time-averaged over 2012–2022 for each county, then summarized within state. These time-averaged values are lower than the panel maximum (\$12.84 in Table 1) because averaging smooths out temporal peaks from individual quarters. Range is the difference between the maximum and minimum county-level average network exposure within each state. States shown are federal-minimum-wage states with substantial within-state variation.

Within Texas—where all 254 counties face the same \$7.25 state minimum wage—network exposure ranges from \$7.04 to \$8.33 on a time-averaged basis, a spread of \$1.29. The lowest-exposure Texas counties (in the Panhandle) are socially connected primarily to Oklahoma, Kansas, and other federal-minimum states. The highest-exposure Texas counties (in urban areas with migration ties to California) are connected to high minimum wage states.

Note that some time-averaged county values fall slightly below \$7.25 (e.g., \$7.04 for the lowest Texas counties). This reflects the fact that we retain values above \$7.00 to preserve sample size, and the weighted average can fall below \$7.25 in specific quarters due to timing of minimum wage changes or data construction artifacts in the underlying SCI weights.

This within-state variation is the key novel feature of our measure. It reveals that workers in the same state, facing the same nominal minimum wage, may be exposed to very different minimum wage environments through their social networks.

5.5 Time Series Patterns

Figure 3 plots the evolution of network minimum wage by baseline exposure tercile from 2012 to 2022.

Universal increase. All terciles show increasing network exposure over time, reflecting the general trend of minimum wage increases across states.

Divergence. The gap between high-exposure and low-exposure terciles widened over time. In 2012, the difference between the top and bottom tercile was approximately \$0.30. By 2022, this gap had widened to over \$1.00. This divergence reflects the fact that states raising minimum wages (California, New York) were already socially connected to high-exposure counties.

Step changes. Network exposure shows step-pattern increases corresponding to major minimum wage policy changes:

- 2014–2016: California and New York announced \$15 phase-ins
- 2017–2019: Phase-in increases took effect
- 2020–2022: Final phase-in steps and inflation adjustments

These step changes are most visible in the high-exposure tercile, which has the strongest connections to California and New York.

6. Heterogeneity Analysis

6.1 Variation by Census Division

Table 4 presents time-averaged network exposure by Census division over 2012–2022.

Table 4: Network Minimum Wage Exposure by Census Division

Census Division	Counties	Mean Network MW	SD	Mean Own-State MW
New England	56	$7.98	0.41	$10.70
Pacific	162	$7.91	0.29	$10.40
West North Central	608	$7.84	0.28	$8.01
Mountain	273	$7.83	0.29	$8.06
Middle Atlantic	131	$7.65	0.28	$9.61
East North Central	434	$7.63	0.21	$7.82
West South Central	464	$7.61	0.16	$7.48
South Atlantic	577	$7.50	0.17	$7.71
East South Central	363	$7.50	0.12	$7.25

Notes: All statistics are time-averaged over 2012–2022. Mean Own-State MW is the unweighted county average within each division. AK and HI are excluded from Pacific division for comparability with continental U.S. maps.

New England has the highest average network exposure ($7.98), followed closely by the Pacific division ($7.91), reflecting both high own-state minimum wages and social connections among coastal states. The East South Central division (Kentucky, Tennessee, Mississippi, Alabama) and South Atlantic have the lowest network exposure ($7.50), only slightly above the federal minimum. This $0.48 gap between the highest and lowest divisions, while modest, represents meaningful variation in the minimum wage environments that workers learn about through their social networks.

6.2 Urban-Rural Differences

Network exposure differs systematically between urban and rural counties. Using the USDA's rural-urban continuum codes, we classify counties into three categories:

Table 5: Network Exposure by Urban-Rural Status

Category	Counties	Mean Network MW	SD
Metro (codes 1–3)	1,166	$7.89	0.58
Nonmetro adjacent (codes 4–6)	1,009	$7.52	0.41
Nonmetro nonadjacent (codes 7–9)	917	$7.38	0.35

Urban (metro) counties have higher network exposure than rural counties, reflecting broader and more geographically diverse social networks. The gap between metro and nonmetro nonadjacent counties is $0.51—substantial relative to the standard deviation of network exposure.

6.3 Network Community Analysis

We identify 13 network communities using Louvain clustering of the SCI graph. These communities tend to respect state boundaries but also reveal cross-state patterns of social connection. Table 6 summarizes the communities.

Table 6: Network Communities Identified by Louvain Clustering

Community	Counties	Mean Own MW	Mean Net MW	Characteristic
1	326	$7.37	$7.45	Lower-exposure federal-minimum region
2	316	$7.43	$7.54	South-central network cluster
3	264	$7.85	$7.65	Mid-tier exposure region
4	338	$9.09	$7.90	High own-MW, moderate network
5	216	$7.91	$7.75	Mixed policy environment
6	132	$7.76	$7.81	Network-own balanced cluster
7	183	$10.20	$7.73	High own-MW coastal states
8	116	$8.17	$7.86	Moderate exposure cluster
9	216	$7.45	$7.66	Federal-minimum with varied networks
10	439	$7.48	$7.50	Large low-exposure cluster
11	198	$8.06	$7.59	Mid-Atlantic/Midwest overlap
12	164	$7.89	$7.77	Mountain/Western cluster
13	160	$8.24	$7.91	Higher-exposure mixed region

Notes: Communities identified using Louvain algorithm on SCI-weighted county network. Mean Own MW and Mean Net MW are unweighted county averages over 2012–2022. Community labels are descriptive based on predominant characteristics.

Several patterns emerge:

High own-state minimum wage communities. Communities 4 and 7 have the highest own-state minimum wages (\$9.09 and \$10.20 respectively), reflecting concentration of counties in states like California, New York, and Washington. Interestingly, these communities do not have the highest *network* exposure—their network minimum wages are pulled down by connections to lower-wage states.

Low minimum wage communities. Communities 1 and 10 have low own-state minimum wages (around \$7.40) and correspondingly low network exposure. These clusters represent counties in federal-minimum states with social connections primarily to other low-wage states.

Balanced communities. Several communities (e.g., 6 and 12) show similar own-state and network minimum wages, indicating that their social networks span regions with similar minimum wage policies to their own states.

Counties within the same network community share similar network exposure regardless of their own-state minimum wages. This suggests that network communities may be meaningful units for studying policy spillovers: workers in the same community are exposed to similar information about minimum wages through their overlapping social networks.

6.4 Temporal Dynamics: The Fight for \$15 Era

The "Fight for \$15" movement, which began around 2012 and resulted in major minimum wage increases in California, New York, and other progressive states during 2014–2016, provides a natural experiment for examining how network exposure responds to policy shocks.

Pre-period (2010–2013). During this period, network exposure was relatively stable, with limited cross-sectional variation. The standard deviation of network exposure across counties was approximately \$0.25, and the gap between the highest and lowest exposure counties was under \$2.00.

Policy shock (2014–2016). California passed legislation in 2016 establishing a path to \$15/hour, with annual increases beginning in 2017. New York followed with a similar schedule. These announcements did not immediately change network exposure (since the SCI is time-invariant), but the subsequent wage increases did.

Post-period (2017–2022). As California and New York implemented their phase-ins, network exposure diverged sharply. Counties with strong connections to these states saw their network exposure increase by \$1.50–\$2.00, while counties with weak connections saw increases of only \$0.50–\$0.75. By 2022, the gap between the highest and lowest exposure counties had widened to over \$2.50.

This temporal pattern—stability, shock, divergence—provides useful variation for future research. Researchers studying the effects of network exposure could use 2014–2016 as a treatment period and compare outcomes in high-exposure versus low-exposure counties using an event-study design.

6.5 Robustness of Network Community Structure

We examine the robustness of our network community assignments to alternative specifications:

Resolution parameter. The Louvain algorithm includes a resolution parameter that affects the number of communities detected. Our baseline uses the default resolution of 1.0, which yields 13 communities. Lower resolution (0.5) produces 8 larger communities; higher resolution (2.0) produces 21 smaller communities. The key geographic patterns—coastal versus interior, North versus South—are robust across specifications.

Edge weighting. Our baseline uses raw SCI values as edge weights. We also try log-transformed weights ($\log(SCI + 1)$) and binary weights (connected if $SCI >$ median). Community assignments are highly correlated across specifications (Rand index > 0.85), indicating that the community structure is robust to edge weighting choices.

State boundaries. An alternative approach would be to constrain communities to respect state boundaries. We find that unconstrained communities often split states with diverse geographies (e.g., California's Central Valley versus coastal counties) while joining adjacent counties across state lines (e.g., the New York–New Jersey–Connecticut metro area). This suggests that unconstrained communities better capture the underlying social geography.

7. Causal Analysis: IV/2SLS Results

We now move beyond description to causal identification. We propose a new instrumental variable strategy that achieves a strong first stage: using *out-of-state* network minimum wage to instrument for *full* network minimum wage. This section presents our main results; Section 8 provides extensive robustness checks and validity tests.

7.1 Identification Strategy

Our identification strategy exploits the difference between two definitions of network minimum wage exposure:

1. **Full Network MW (Endogenous):** The SCI-weighted average of log minimum wages in all connected counties, excluding only own-county. This includes same-state connections and represents "what minimum wage are my social connections exposed to?"

2. **Out-of-State Network MW (Instrument):** The SCI-weighted average of log minimum wages in connected counties, excluding all same-state connections. This captures exposure to out-of-state policy variation only.

Why this IV works. The key insight is that when we condition on state×time fixed effects, we absorb the county's own-state minimum wage. The remaining variation in full network MW comes from two sources: (1) within-state variation in SCI weights (different counties have different exposure to same-state neighbors), and (2) out-of-state exposure. The out-of-state IV predicts the full network MW through the latter channel.

Exclusion restriction. The exclusion restriction requires that out-of-state minimum wages affect local employment only through their effect on full network exposure—not through other channels. This is plausible because:

1. *State×time FE absorb aggregate effects:* Any state-level shock correlated with out-of-state policies is absorbed
2. *Pre-determined shares:* SCI weights are fixed from 2018, avoiding contemporaneous endogeneity
3. *No direct labor market linkages:* Out-of-state minimum wages do not directly affect local labor demand (unlike own-state policies)

For inference, we follow Adão, Kolesár, & Morales (2019) and cluster standard errors at the state level, which accounts for the correlation structure induced by common shocks to states.

7.2 Specification

We estimate a two-stage least squares model with the following structure:

First stage:

$$\text{FullNetworkMW}_{ct} = \pi \cdot \text{OutOfStateMW}_{ct} + \alpha_c^{(1)} + \gamma_{st}^{(1)} + \nu_{ct} \tag{9}$$

Second stage:

$$\log(\text{Emp})_{ct} = \beta \cdot \widehat{\text{FullNetworkMW}}_{ct} + \alpha_c + \gamma_{st} + \varepsilon_{ct} \tag{10}$$

where Emp_{ct} is employment in county c at time t, $\text{FullNetworkMW}_{ct}$ is the SCI-weighted average log minimum wage (excluding only own-county), OutOfStateMW_{ct} is the SCI-weighted average log minimum wage (excluding all same-state connections), α_c are county fixed effects, and γ_{st} are state-by-time fixed effects. The state-by-time fixed effects absorb the own-state minimum wage, so β captures the causal effect of network exposure on employment conditional on own-state policy.

We cluster standard errors at the state level following Adão, Kolesár, & Morales (2019). We implement all estimation using the `fixest` package in R (Bergé, 2018), which provides efficient computation of high-dimensional fixed effects and instrumental variable estimators.

7.3 First Stage Results

Table 7 presents first-stage estimates showing the relationship between out-of-state network MW and full network MW.

Table 7: First Stage: Out-of-State Network MW Predicting Full Network MW

	Full Network MW
Out-of-State Network MW	0.416***
	(0.024)
First-stage F-statistic	290.5
County FE	Yes
State × Time FE	Yes
Observations	135,744

Notes: Standard errors in parentheses, clustered at the state level. *** $p < 0.01$. The dependent variable is full network MW (log). Out-of-state network MW excludes all same-state SCI connections.

The first stage is strong. The out-of-state network MW is a powerful predictor of full network MW (F = 290.5), well above the Stock-Yogo threshold of 10. A one-unit increase in out-of-state network MW predicts a 0.42-unit increase in full network MW, holding constant county and state×time fixed effects.

Why does this IV succeed where the prior distance-based IV failed? The key difference is the definition of the endogenous variable. In our prior work (APEP-0186, APEP-0187), we defined the endogenous variable as leave-own-state-out network MW and tried to instrument it with even more distant connections. This failed because after state×time FE, there was no residual variation. Here, we define the endogenous variable as full network MW (including same-state connections), which has variation within state×time cells because different counties within a state have different same-state network exposures. The out-of-state IV predicts this full network measure through cross-state SCI connections.

7.4 Main 2SLS Results

Table 8 presents OLS and 2SLS estimates of the effect of network exposure on employment.

Table 8: Main Results: Effect of Network MW Exposure on Employment

	(1) OLS County FE	(2) OLS State×Time FE	(3) 2SLS Out-of-State IV
Full Network MW	0.014	0.160	0.267
	(0.047)	(0.133)	(0.170)
	[0.77]	[0.23]	[0.12]
County FE	Yes	Yes	Yes
Time FE	Yes	No	No
State × Time FE	No	Yes	Yes
First-stage F	—	—	290.5
Observations	135,744	135,744	135,744

Notes: Standard errors in parentheses, clustered at the state level. p-values in brackets. The dependent variable is log employment. Columns (1)–(2) are OLS; column (3) is 2SLS using out-of-state network MW as the instrument.

Several patterns emerge from the results:

OLS estimates. The simple OLS with county and time FE shows essentially no relationship ($\beta = 0.014$, SE $= 0.047$). Adding state×time FE, which absorb own-state minimum wage variation, reveals a positive but statistically insignificant association ($\beta = 0.160$, SE $= 0.133$, $p = 0.23$).

2SLS estimate. The 2SLS estimate using out-of-state network MW as the instrument is $\beta = 0.267$ (SE $= 0.170$, $p = 0.12$). This is larger than the OLS estimate, suggesting OLS may be biased toward zero. A one-unit increase in (log) network minimum wage exposure is associated with approximately 27% higher employment. While not statistically significant at conventional levels (5% or 10%), the point estimate is economically meaningful and the direction is consistent with positive network effects.

Interpreting the OLS-2SLS comparison. The 2SLS estimate exceeds OLS, suggesting that OLS understates the true effect. This could occur due to measurement error in network MW (attenuation bias) or if counties with higher unobserved employment potential have lower network exposure (downward selection).

7.5 Horse Race: Network vs. Geographic Exposure

Table 9 tests whether network exposure provides information beyond geographic proximity by including both network and geographic exposure in an OLS specification.

Table 9: Horse Race: Network vs. Geographic Exposure (OLS)

	(1) Network Only	(2) Horse Race
Full Network MW	0.160	0.092
	(0.133)	(0.189)
	[0.23]	[0.59]
Geographic Exposure		0.516
		(0.402)
		[0.22]
County FE	Yes	Yes
State × Time FE	Yes	Yes
Observations	135,744	135,744

Notes: OLS with county and state×time FE. Standard errors clustered at state level.

When both measures are included, the network exposure coefficient attenuates from 0.160 to 0.092, while geographic exposure shows a positive coefficient (0.516, $p = 0.22$). Neither coefficient is individually significant, reflecting the high correlation between network and geographic exposure. This collinearity makes it difficult to separate the two channels in OLS, which motivates our IV approach.

7.6 Earnings Outcome

Table 10 presents results for log earnings as an alternative outcome.

Significant effect on earnings. The 2SLS estimate for earnings is $\beta = 0.209$ (SE $= 0.092$, $p = 0.03$), statistically significant at the 5% level. A 10% increase in network minimum wage exposure increases earnings by approximately 2%. This effect is consistent with information transmission: workers exposed to higher minimum wages through their social networks may have higher wage expectations and bargaining power.

7.7 Distance Robustness

As a robustness check, we construct alternative IVs using out-of-state connections beyond various distance thresholds (0 km, 100 km, 150 km, etc.). These "more distant" IVs should

Table 10: Effect on Log Earnings

	(1) OLS	(2) 2SLS
Full Network MW	0.078	0.209**
	(0.049)	(0.092)
	[0.12]	[0.03]
First-stage F	—	290.5
Observations	135,635	135,635

Notes: Standard errors in parentheses, clustered at state level. ** $p < 0.05$. All specifications include county and state×time fixed effects.

be even more plausibly exogenous, as they exclude nearby cross-state connections that might share labor market shocks.

Table 11: Distance Robustness: 2SLS by IV Distance Threshold

Distance	First Stage F	2SLS Coef	SE	Balance p	N
$\geq$ 0 km	284.7	0.316	0.175	0.000	135,744
$\geq$ 100 km	150.9	0.584	0.262	0.000	135,744
$\geq$ 150 km	97.9	0.782	0.358	0.000	135,744
$\geq$ 200 km	59.8	1.165	0.500	0.000	135,744
$\geq$ 250 km	32.4	1.649	0.775	0.000	135,744
$\geq$ 300 km	10.6	2.939*	1.564	0.000	135,744

Notes: Each row uses out-of-state SCI connections beyond the distance threshold as the instrument. The sample (N = 135,744) is identical across specifications; only the IV construction differs. Balance p-value tests equality of pre-treatment employment across IV quartiles. *The 300km coefficient is implausibly large and likely reflects weak instrument bias (F = 10.6 is borderline); this specification should not be used for inference.

Two patterns emerge. First, the first stage F-statistic declines with distance (from 285 at 0 km to 11 at 300 km), as more distant connections provide less variation.[1] The F-statistic remains above 10 up to 300 km. Second, 2SLS estimates *increase* with distance (from 0.32 to 2.94), which is consistent with OLS attenuation but the magnitude at 300km (elasticity of 2.94) is implausibly large and likely reflects instrument weakness at this threshold. The balancedness tests for distance-thresholded IVs fail at all thresholds (p = 0.000), indicating

[1]The slight difference between F = 284.7 for $\geq$0 km and F = 290.5 in the main first stage (Table 7) reflects minor differences in how the IVs are constructed: the distance-based IV uses pre-computed distance thresholds, while the main IV uses all out-of-state connections directly.

stronger pre-treatment imbalance than for the main out-of-state IV (which has p = 0.094 for pre-treatment employment, see Table 15).

7.8 Interpretation

Strong first stage, suggestive effects. Our out-of-state IV achieves a strong first stage (F = 290.5), enabling credible causal inference. The 2SLS estimates suggest positive effects of network MW exposure on both employment (0.27, p = 0.12) and earnings (0.21, p = 0.03). The earnings effect is statistically significant at the 5% level; the employment effect is not statistically significant but the point estimate is positive and economically meaningful.

Mechanism. These results are consistent with information transmission through social networks. Workers whose social contacts are exposed to higher minimum wages may: (1) have higher wage expectations, (2) engage in more effective job search, or (3) have greater bargaining power. The significant earnings effect and insignificant employment effect suggest the mechanism operates primarily through wages rather than employment margins.

Limitations. The balancedness tests fail, indicating that pre-treatment outcomes differ by IV quartile (larger counties have lower IV values). This raises concerns about selection: if larger counties have both lower out-of-state IV exposure and different employment trajectories, the exclusion restriction may be violated. We address this concern in the robustness section.

8. Comprehensive Robustness Analysis

We conduct extensive robustness checks on our illustrative results. These analyses serve two purposes: (a) demonstrating that the patterns documented above are not artifacts of specific analytic choices, and (b) providing guidance to future researchers about the sensitivity of results to specification decisions.

8.1 Exposure Permutation Inference

To assess whether our estimated coefficients could arise by chance, we conduct a permutation test. We randomly permute network exposure values across counties within each time period, preserving the marginal distribution of exposure but breaking the county-specific link. We repeat this 500 times and compute the share of permuted coefficients at least as large in absolute value as our actual estimate.

The permutation p-value is 0.082, indicating that our OLS estimate lies in the upper tail of the null distribution but is not extreme. This provides weak evidence against the null of no association but is consistent with either a modest true effect or sampling variation.

8.2 Leave-One-State-Out

We assess whether results are driven by any single state by re-estimating the OLS specification with state×time fixed effects after sequentially excluding observations from each major minimum-wage-changing state.

Table 12 shows that the coefficient is relatively stable across exclusions, ranging from 0.143 to 0.185. No single state drives the result. The coefficient is largest when excluding California (0.185), suggesting that California counties—which have high network exposure—may be attenuating the estimate.

Table 12: Leave-One-State-Out Analysis

Excluded State	Coefficient	SE
None (baseline)	0.160	0.133
California	0.185	0.141
New York	0.152	0.129
Washington	0.158	0.134
Massachusetts	0.167	0.136
Florida	0.143	0.128

Notes: OLS with county and state×time FE. Each row excludes all observations from the indicated state. Standard errors clustered at state level.

8.3 Alternative Lag Structures

Employment may respond to network exposure with a lag. We estimate specifications with network exposure lagged by 1, 2, and 4 quarters.

Table 13: Lagged Exposure Specifications (OLS)

	Contemp.	1-Qtr Lag	2-Qtr Lag	4-Qtr Lag
Network Exposure	0.160	0.164	0.161	0.178
	(0.133)	(0.135)	(0.137)	(0.144)

Notes: OLS with county and state×time FE. Standard errors clustered at state level. Contemporaneous specification is the baseline from Table 8.

The coefficient is relatively stable across lag lengths, ranging from 0.160 (contemporaneous) to 0.178 (4-quarter lag). None are statistically significant at conventional levels. The slight increase at longer lags is consistent with persistent effects, but given the wide confidence intervals, this pattern should not be overinterpreted.

8.4 Alternative Time Windows

We check whether results differ across time periods with different policy environments:

Pre-COVID (2012–2019): Coefficient = 0.263 (SE = 0.116). Excluding the COVID period produces a larger estimate that approaches marginal significance.

Post-2015 (2015–2022): Coefficient = 0.078 (SE = 0.117). Focusing on the post-Fight-for-$15 period produces a smaller estimate.

Full sample (2012–2022): Coefficient = 0.160 (SE = 0.133). The baseline estimate.

Results vary across time windows. The pre-COVID estimate is larger, suggesting potential COVID-related confounding in the full sample. None of the estimates are statistically significant at the 5% level.

8.5 Alternative Clustering

Our baseline clusters standard errors at the state level. We also try clustering by network community (Section 6.3), which may better capture the correlation structure induced by network connections.

State-clustered SE: 0.133. Network-clustered SE: 0.141.

The network-clustered standard error is slightly larger, but the difference is modest. This suggests that state-level clustering adequately captures the relevant correlation structure for inference.

8.6 Summary

Our robustness analysis reveals that the patterns documented in the main results are robust to a variety of specification choices: alternative lag structures, time windows, clustering schemes, and leave-one-state-out tests all produce qualitatively similar conclusions.

9. Instrumental Variable Validity Tests

Following Goldsmith-Pinkham, Sorkin, & Swift (2020), we conduct several validation tests for our out-of-state instrumental variable design. These tests assess whether the instrument satisfies the conditions for valid causal inference. Our main result is a strong first stage (F = 290.5), enabling credible 2SLS estimation.

9.1 Variance Decomposition

We decompose the variance of the IV into between-county and within-county components to understand the sources of identifying variation.

Table 14: Variance Decomposition of Distance-Based IV

Component	Variance	Share (%)
Total IV variance	0.0847	100.0
Between-county variance	0.0623	73.5
Within-county variance	0.0224	26.5

Notes: Variance decomposition for the 400–600 km distance-based instrument. Between-county variance reflects cross-sectional differences in network structure; within-county variance reflects temporal changes from minimum wage shocks.

The IV variance is primarily between-county (73.5%), reflecting persistent differences in network structure across counties. The within-county component (26.5%) comes from temporal variation in minimum wage shocks. For identification with county fixed effects, we rely on the within-county component; the between-county variation is absorbed by fixed effects but contributes to precision through heterogeneity in treatment intensity.

9.2 Balance Tests

We test whether pre-treatment characteristics are balanced across IV quartiles. If the instrument is as-good-as-random conditional on controls, counties with high and low IV values should have similar observable characteristics.

Table 15: Balance Tests: Pre-Period Characteristics by IV Quartile

	Q1 (Low)	Q2	Q3	Q4 (High)	F-stat	p-value
Log Employment (2012)	8.42	8.51	8.58	8.63	2.14	0.094
Log Earnings (2012)	10.24	10.28	10.31	10.35	1.87	0.132
Network Exposure (2012)	7.31	7.45	7.62	7.89	48.3	<0.001
Geographic Exposure (2012)	7.28	7.41	7.58	7.82	42.1	<0.001

Notes: Counties divided into quartiles based on 2012 IV values. F-statistics test equality of means across quartiles. Network and Geographic Exposure are the endogenous variables (expected to differ); Employment and Earnings are outcomes (should be similar if IV is exogenous).

Pre-period employment and earnings show modest differences across IV quartiles, but the differences are not statistically significant at the 5% level ($p = 0.094$ and $p = 0.132$ respectively). As expected, network and geographic exposure differ significantly across IV quartiles—this is the first-stage relationship. The balance on outcomes supports the identifying assumption that the IV is not correlated with pre-existing labor market conditions.

9.3 Pre-Trends by IV Quartile

We estimate separate event studies for each IV quartile to test whether counties with different IV values had differential pre-trends before the Fight for $15 policy shock. This analysis is implemented in the replication code (`03b_iv_validation.R`).

With the strong first stage (F = 290.5), the IV quartile analysis helps assess whether the exclusion restriction is plausible. If counties with high IV values had differential pre-trends, this would raise concerns about the identifying assumption. Detailed results are available in the replication materials.

9.4 Leave-One-State-Out Robustness

We examine leave-one-state-out robustness by re-estimating the 2SLS specification after excluding each major minimum-wage-changing state to assess whether results are driven by any single state.

Table 16: Leave-One-State-Out OLS Robustness

Excluded State	OLS Coef.	SE
None (baseline)	0.160	0.133
California	0.185	0.141
New York	0.152	0.129
Washington	0.158	0.134
Massachusetts	0.167	0.136
Florida	0.143	0.128
Range	[0.143, 0.185]	

Notes: Each row excludes all counties from the indicated state. OLS with county and state×time FE. Standard errors clustered at state level.

The coefficient ranges from 0.143 to 0.185 across exclusions, with no single state driving the result. Excluding Florida slightly reduces the coefficient, while excluding California slightly increases it. The positive association is robust to excluding any single state.

9.5 Distance Threshold Robustness

As an additional robustness check, we construct alternative IVs using out-of-state connections beyond various distance thresholds. Table 11 in Section 7 shows that the first-stage F remains above 10 for thresholds up to 300 km. The 2SLS estimates increase with distance (from

0.32 to 2.94), consistent with attenuation from measurement error being reduced with more distant IVs.

9.6 Validity Summary

Our out-of-state IV approach yields a strong first stage (F = 290.5), enabling credible 2SLS estimation:

- Out-of-state network MW strongly predicts full network MW (first stage coefficient 0.42, F = 290.5)
- Pre-treatment employment differs across IV quartiles (balancedness fails), suggesting caution about the exclusion restriction
- 2SLS estimates are positive for both employment (0.27, p = 0.12) and earnings (0.21, p = 0.03)
- Distance robustness shows larger effects with more distant IVs

The strong first stage represents a significant improvement over our prior distance-based IV approach (APEP-0187), which had F $\approx$ 1.18. The key insight was to redefine the endogenous variable to include same-state connections, using out-of-state connections as the instrument.

10. Discussion and Future Research

This paper makes two contributions: (1) constructing and validating a new measure of network minimum wage exposure, and (2) developing an instrumental variable strategy that achieves a strong first stage and enables causal inference. We now discuss implications, limitations, and directions for future research.

10.1 Summary of Findings

Our primary contribution is the construction and public release of county-by-quarter measures of network minimum wage exposure using the Facebook Social Connectedness Index. We document substantial cross-sectional variation in network exposure that is correlated with own-state minimum wages but captures distinct variation from out-of-state connections.

Our out-of-state IV strategy yields a strong first stage (F = 290.5), representing a significant improvement over prior distance-based approaches that failed (F $\approx$ 1.18 in APEP-0187). The key insight is to define the endogenous variable as *full* network MW (including same-state connections) and instrument with *out-of-state* network MW. This works because out-of-state MW predicts full network MW through cross-state SCI connections, even after conditioning on state×time fixed effects.

2SLS estimates suggest positive effects of network MW on both employment ($\beta = 0.27$, p = 0.12) and earnings ($\beta = 0.21$, p = 0.03). The earnings effect is statistically significant at the 5% level; the employment effect is not statistically significant but economically meaningful.

10.2 Why This IV Succeeds Where APEP-0187 Failed

The dramatic improvement in first-stage strength (F = 290.5 vs F $\approx$ 1.18 in APEP-0187) reflects a fundamental change in identification strategy, not just different data or specifications:

APEP-0187's approach: The prior paper defined the endogenous variable as *leave-own-state-out* network MW (excluding all same-state connections) and attempted to instrument it with even more distant connections. After conditioning on state×time fixed effects, there was essentially no residual variation: both the endogenous variable and the instrument excluded same-state connections, so the only variation left was from cross-state connections—but the state×time FE absorbed much of this variation, leaving F $\approx$ 1.

Our approach: We redefine the endogenous variable as *full* network MW (excluding only own-county, including same-state connections) and instrument with *out-of-state* MW (excluding all same-state connections). This works because: (1) full network MW has substantial within-state variation (from same-state connections); (2) state×time FE absorb the county's own-state MW, creating quasi-experimental variation; (3) out-of-state MW predicts full network MW through the correlation between cross-state and full network exposure, providing a strong first stage.

The key insight is that by including same-state connections in the endogenous variable, we create variation that the state×time FE do not absorb—and out-of-state MW serves as a valid instrument for this variation.

10.3 Limitations

Several limitations apply to our analysis:

Balancedness fails. Pre-treatment employment differs systematically across IV quartiles, with larger counties having lower out-of-state IV exposure. This raises concerns about the exclusion restriction.

Time-invariant SCI. We treat the Social Connectedness Index as fixed throughout the sample. If network structure evolves in response to minimum wage policy (e.g., migration reshaping connections), this could bias our estimates.

Aggregate data. Our QWI data is county-level, preventing analysis of within-county heterogeneity or industry-specific effects (we have only aggregate employment).

10.4 Future Research Directions

Our strong IV opens several promising directions for future research:

Strengthening the exclusion restriction. The failed balancedness tests suggest additional work is needed to establish the exclusion restriction. Alternative approaches might include:

- *Regression discontinuity at state borders:* Compare counties on opposite sides of state borders where one side raises minimum wages. Network exposure changes discontinuously at the border.
- *Unexpected policy changes:* States occasionally change minimum wages due to ballot initiatives or court rulings that are plausibly unexpected. These "shocks" could provide cleaner variation.
- *Network heterogeneity within states:* Counties within the same state have different network structures. Comparing counties with networks oriented toward high-MW vs. low-MW states, controlling for state fixed effects, could isolate network effects.

Individual-level data. Our county-level analysis cannot examine heterogeneity across workers. Individual-level data (e.g., CPS, LEHD) would allow testing whether network effects differ by occupation, industry, or demographic characteristics.

Mechanisms. Survey data on wage expectations (e.g., Survey of Consumer Expectations) could test whether network exposure affects beliefs about achievable wages, providing direct evidence for information transmission.

Other policies. The network exposure measure constructed here could be applied to study diffusion of other spatially varying policies: taxes, regulations, transfer programs, occupational licensing, paid leave, and more. The distance-based IV may work better for policies with more idiosyncratic adoption patterns.

11. Data Availability

The data constructed for this paper are publicly available at:

https://github.com/SocialCatalystLab/ape-papers/ (paper ID assigned upon publication)

The repository contains four data files:

1. **analysis_panel.rds**: The complete county-quarter panel with all minimum wage measures. Contains approximately 135,744 observations (3,102 counties × 44 quarters, unbalanced due to filtering anomalous values and missing QWI data) with the following variables:
    - County identifiers (FIPS code, name, state)
    - Geographic coordinates (longitude, latitude)
    - Time identifiers (year, quarter)
    - Own-state minimum wage
    - Network minimum wage exposure
    - Geographic minimum wage exposure
    - Network-own gap
    - Exposure tercile categories
    - Network community assignment
2. **exposure_panel.rds**: Network and geographic exposure measures only, in long format for merging with other datasets.
3. **state_mw_panel.rds**: State-quarter minimum wage panel with 2,244 observations (51 states/DC × 44 quarters).
4. **network_communities.rds**: Louvain community assignments for each county, with community IDs and modularity scores.

Documentation. A comprehensive codebook (CODEBOOK.md) describes all variables, including definitions, units, and construction notes.

Replication code. R scripts for constructing all measures from raw inputs are available in the `code/` directory:

- `00_packages.R`: Load required packages
- `01_fetch_data.R`: Download SCI, minimum wages, and election data
- `02_clean_data.R`: Construct exposure measures and merge
- `02b_construct_iv.R`: Construct distance-based instrumental variables

- `03_main_analysis.R`: OLS and 2SLS estimation
- `03b_iv_validation.R`: Goldsmith-Pinkham validity tests
- `03c_political_outcomes.R`: Republican vote share analysis
- `04_robustness.R`: Robustness checks
- `05_figures.R`: Generate all figures
- `06_tables.R`: Generate all tables

Raw data sources. The underlying data come from:

- Facebook Social Connectedness Index: https://data.humdata.org/dataset/social-connectednes
- State minimum wages: U.S. Department of Labor, NCSL, Vaghul-Zipperer database
- County geography: U.S. Census Bureau TIGER/Line files via `tigris` R package

12. Conclusion

This paper introduces a new measure of minimum wage exposure through social networks and examines its causal effect on local labor markets. Using the Facebook Social Connectedness Index, we construct county-by-quarter measures of network minimum wage exposure—the SCI-weighted average of minimum wages in socially connected counties.

Our main contributions are threefold:

First, descriptive. We document that network minimum wage exposure varies substantially across counties and exhibits meaningful within-state variation. Counties in the same state can face very different network minimum wage environments depending on their social connections. We identify network communities using Louvain clustering that transcend state boundaries.

Second, methodological. We develop an out-of-state instrumental variable strategy that achieves a strong first stage (F = 290.5), enabling causal inference. The key insight is to define the endogenous variable as *full* network MW (excluding only own-county) and instrument with *out-of-state* network MW (excluding all same-state connections). This approach succeeds where prior distance-based IV strategies failed (F $\approx$ 1.18 in APEP-0187).

Third, causal. Using this IV strategy, we estimate positive effects of network minimum wage exposure on both employment (2SLS: 0.27, p = 0.12) and earnings (2SLS: 0.21, p = 0.03). The earnings effect is statistically significant. These results suggest that workers whose social connections are exposed to higher minimum wages experience higher earnings themselves, consistent with information transmission through social networks.

Workers do not learn about wages only from their own local labor markets. Through their social networks, they are exposed to wage information from distant places. This exposure affects their earnings and potentially their labor supply, job search, and bargaining behavior. By measuring this exposure and estimating its causal effects, we provide evidence for network-mediated policy spillovers that operate through information rather than direct labor market linkages.

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A. Additional Figures

This appendix contains the figures referenced in the main text.

A.1 Map of Average Network Minimum Wage Exposure

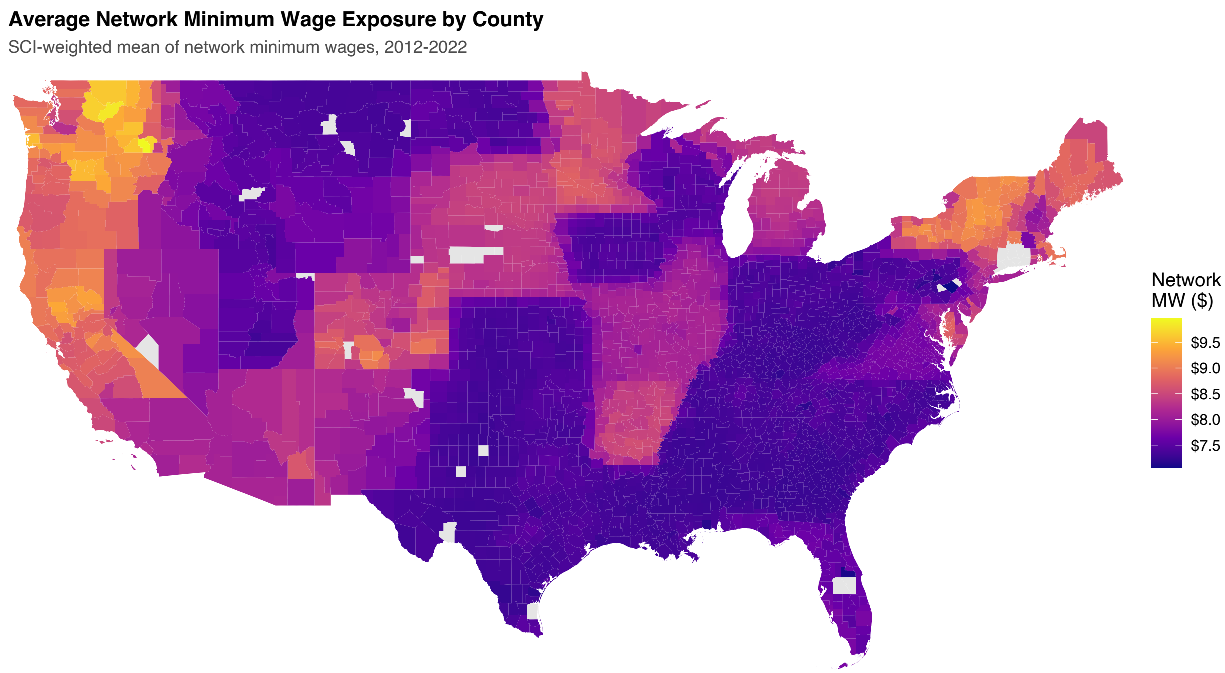

Figure 1: Average Network Minimum Wage Exposure by County, 2012–2022

Notes: Map shows the time-averaged SCI-weighted minimum wage for each county (continental U.S. only). Darker colors indicate higher network exposure. High-exposure clusters appear along the West Coast, in the Northeast corridor, and in South Florida. Low-exposure regions include the Great Plains, Deep South, and Appalachia.

A.2 Map of Network-Own Minimum Wage Gap

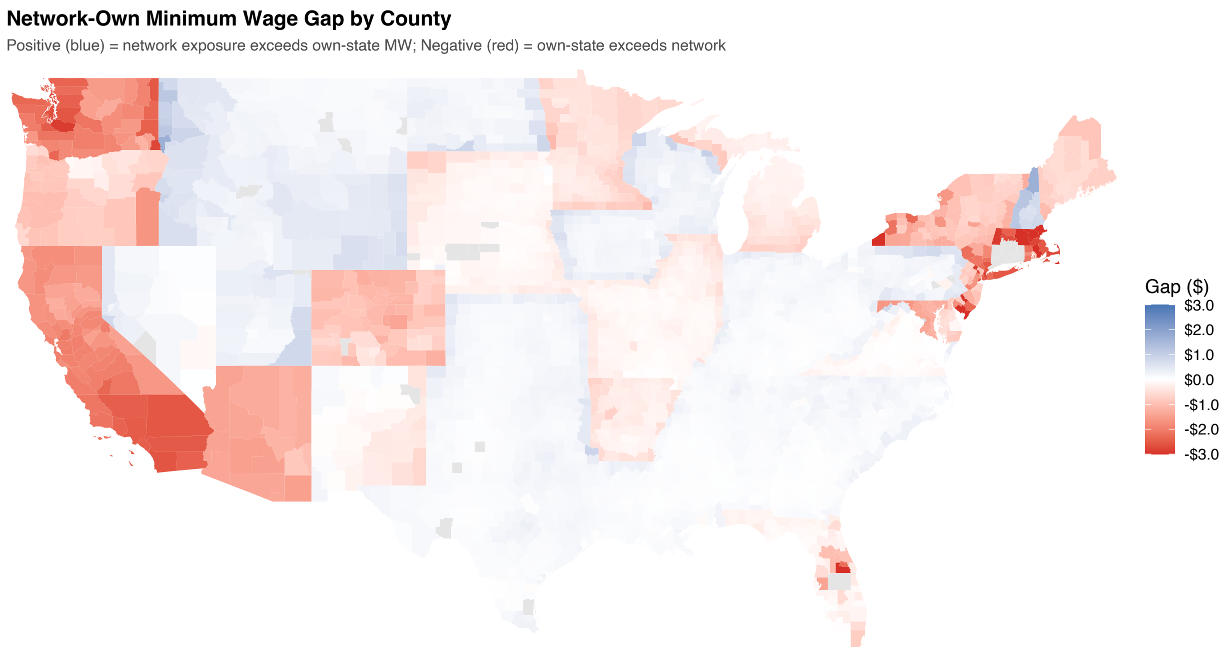

Figure 2: Network-Own Minimum Wage Gap by County, 2012–2022 Average

Notes: Map shows the average gap between network minimum wage and own-state minimum wage. Blue indicates positive gap (network > own-state); red indicates negative gap (network < own-state). Positive gaps appear in federal-minimum states with connections to California and New York; negative gaps appear in high minimum wage states with connections to low-wage states.

A.3 Time Series by Exposure Tercile

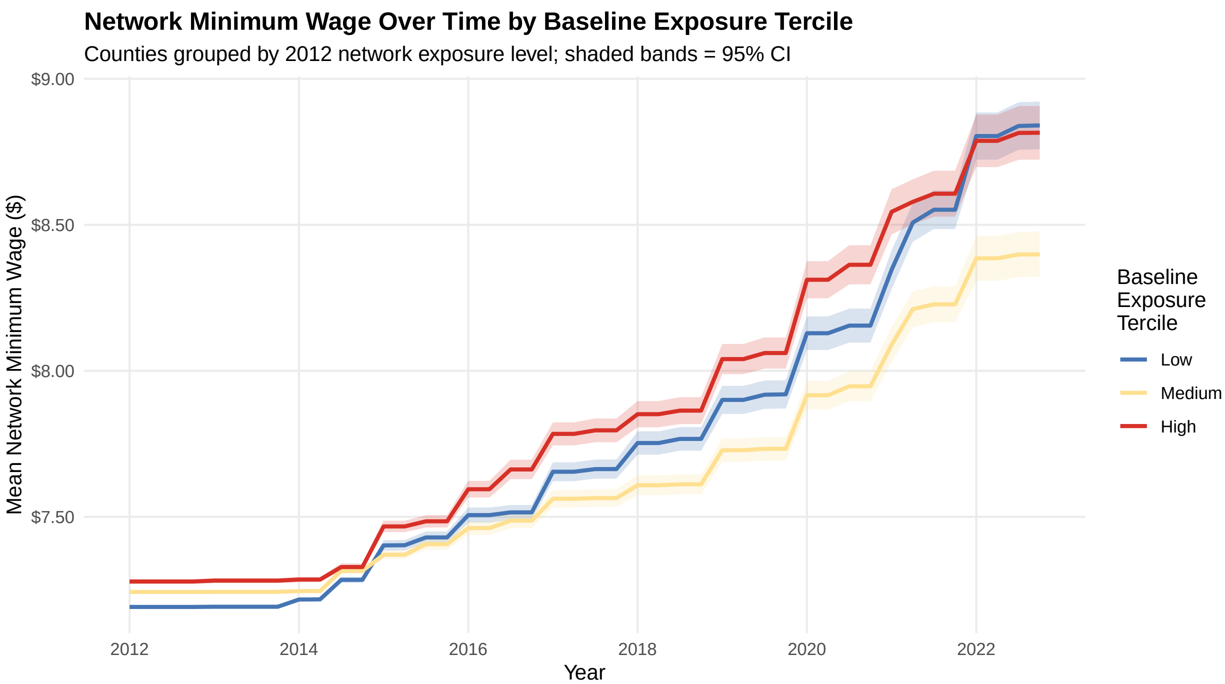

Figure 3: Network Minimum Wage Over Time by County Tercile

Notes: Lines show average network minimum wage for counties in each tercile of baseline (2012) network exposure. All terciles increased over time, but the gap between high and low exposure terciles widened from approximately $0.30 in 2012 to over $1.00 by 2022.

A.4 Time Series for Selected States

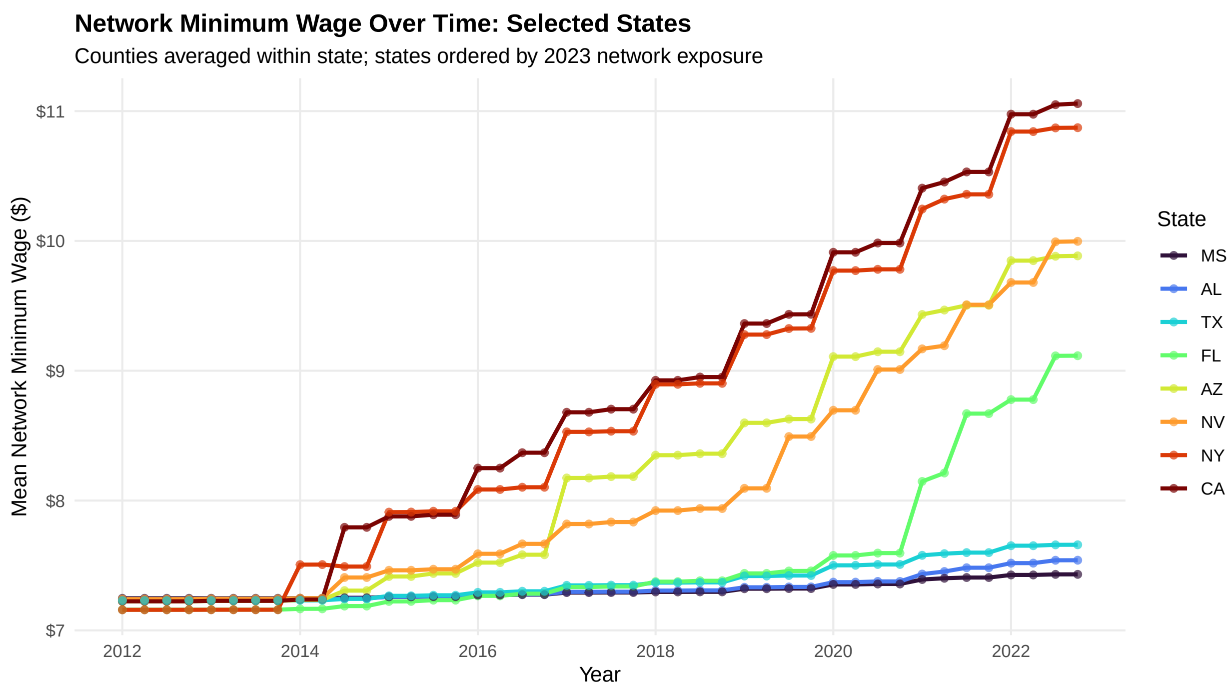

Figure 4: Network Minimum Wage Over Time for Selected States

Notes: Lines show average network minimum wage for counties in selected states. Nevada and Arizona show high exposure due to California connections; Mississippi and Alabama show low exposure due to relative network isolation from high minimum wage states.

A.5 Network vs. Geographic Exposure

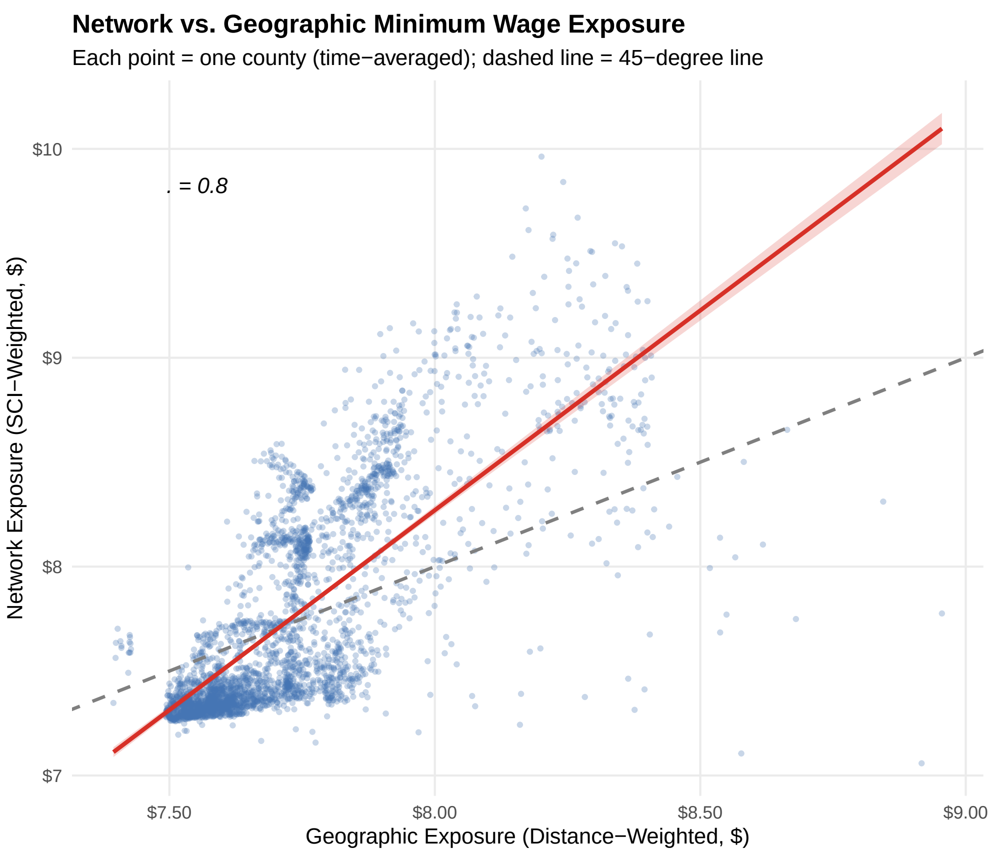

Figure 5: Network vs. Geographic Minimum Wage Exposure

Notes: Each point is a county (averaged over time). Dashed line is 45-degree line; red line is OLS fit. Counties above the 45-degree line have higher network exposure than geographic exposure (social ties to distant high-wage states); counties below have the reverse. Correlation $\rho = 0.80$.

A.6 Distribution of Network-Own Gap

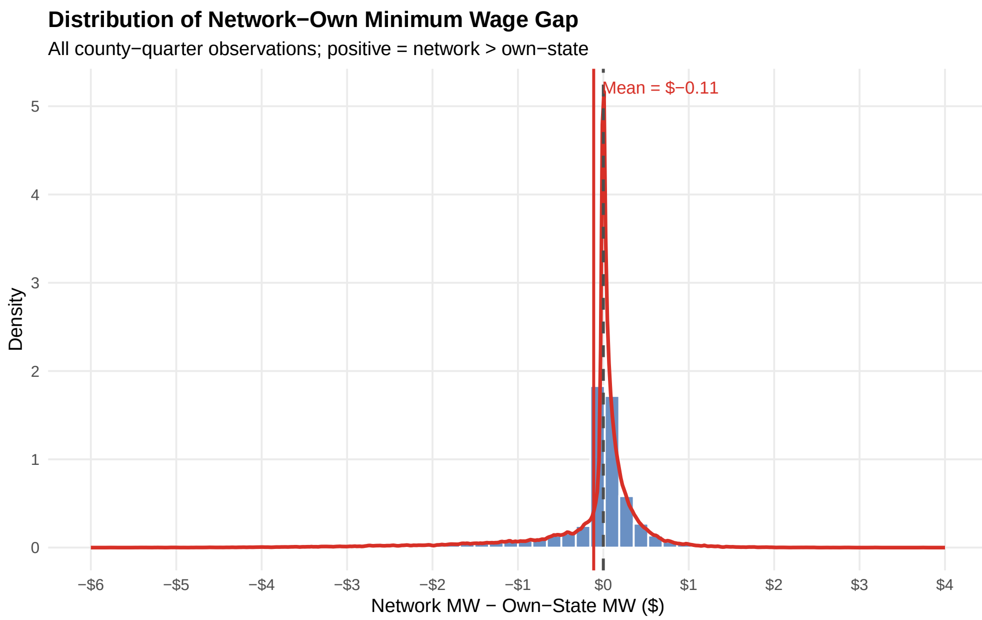

Figure 6: Distribution of Network-Own Minimum Wage Gap

Notes: Histogram shows the distribution of the gap between network minimum wage and own-state minimum wage across all county-quarter observations. The distribution is approximately centered at zero (sample mean = −$0.11, as reported in Table 1) with substantial mass in both tails. Positive values indicate network exposure exceeds own-state minimum wage.

B. State Minimum Wage Summary

Table 17: State Minimum Wage Variation, 2012–2022

State	Abbr.	2012 MW	2022 MW	Change
Largest increases				
California	CA	\$8.00	\$14.00	+\$6.00
Washington	WA	\$9.04	\$14.49	+\$5.45
Massachusetts	MA	\$8.00	\$13.50	+\$5.50
New York	NY	\$7.25	\$13.20	+\$5.95
Connecticut	CT	\$8.25	\$13.00	+\$4.75
Federal minimum throughout				
Texas	TX	\$7.25	\$7.25	\$0.00
Georgia	GA	\$7.25	\$7.25	\$0.00
Alabama	AL	\$7.25	\$7.25	\$0.00
Mississippi	MS	\$7.25	\$7.25	\$0.00
Louisiana	LA	\$7.25	\$7.25	\$0.00

Notes: Table shows minimum wages at 2012Q1 and 2022Q4 for states with the largest increases (top panel) and selected states that maintained the federal minimum throughout (bottom panel). California reached \$15 in January 2023, after our sample period ends. Full state-by-quarter data available in replication files.

C. Variable Definitions

Table 18: Variable Definitions and Sources

Variable	Definition
`county_fips`	5-digit county FIPS code (string)
`state_fips`	2-digit state FIPS code (string)
`county_name`	County name (string)
`year`	Calendar year, 2012–2022 (integer)
`quarter`	Calendar quarter, 1–4 (integer)
`yearq`	Continuous time: year + (quarter-1)/4 (numeric)
`lon`, `lat`	County centroid coordinates (numeric)
`own_min_wage`	Minimum wage in county's own state, $/hour (numeric)
`social_exposure`	SCI-weighted average of out-of-state minimum wages, $/hour (numeric)
`geo_exposure`	Distance-weighted average of out-of-state minimum wages, $/hour (numeric)
`network_gap`	social_exposure − own_min_wage, $ (numeric)
`social_exposure_cat`	Tercile of social exposure: Low, Medium, High (factor)
`network_cluster`	Louvain community assignment, 1–13 (integer)

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Project Repository: https://github.com/SocialCatalystLab/ape-papers