



VULNERABILITY PROPAGATION IN INFORMAL LABOR NETWORKS: A GRAPH-THEORETIC FRAMEWORK FOR DETECTING AND DISRUPTING EXPLOITATION IN THE GIG ECONOMY

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Abstract:

The expansion of platform-based informal labor markets across the developing and developed world has produced a class of workers whose contractual precarity is structurally embedded rather than incidental. This paper proposes a graph-theoretic framework to model these labor markets as weighted directed graphs in which nodes represent workers, employers, and intermediary platforms, and edges encode asymmetric relationships of economic dependency, information inequality, and contractual power. We introduce the concept of vulnerability propagation — a process by which adverse shocks such as wage theft, sudden platform deactivation, or unsafe working conditions spread through the network via contagion dynamics analogous to epidemic spreading models. Drawing on structural hole theory, betweenness centrality, and percolation thresholds, we argue that exploitation is not a random occurrence but a topologically predictable event concentrated at specific network positions. The framework offers a principled basis for policy interventions that target the network architecture itself rather than individual workers or firms, and we illustrate its applicability through a case study of platform-mediated delivery labor markets in urban India.

Keywords: *Graph Theory, Labor Networks, Vulnerability Propagation, Gig Economy, Structural Holes, Betweenness Centrality, Percolation Theory, Social Network Analysis*

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Introduction:

The nature of employment has undergone a structural transformation over the past two decades. The rise of platform capitalism — characterised by app-mediated, on-demand, and contract-based labour arrangements — has systematically decoupled work from the legal protections that once governed the employment relationship. Globally, an estimated 1.57 billion workers operate in informal labour arrangements, a figure that encompasses gig workers in wealthy economies alongside day labourers, domestic workers, and migrant workers across the Global South. What unites these populations is not geography or sector but their relational position within labour market networks: they are peripheral nodes connected to high-degree, resource-dense hubs through edges weighted heavily in favour of the employer or platform.

Existing analyses of labour market inequality tend to be either statistical — focusing on aggregate wage distributions and poverty headcounts — or qualitative, documenting lived experiences of exploitation through ethnographic or interview-based methods. Both traditions yield important insights. Neither, however, captures the relational architecture that makes exploitation not merely possible but, in certain network configurations, structurally inevitable. A worker who depends on a single platform for income, has no peer connections to other workers, and lacks access to alternative employment channels occupies a position of extreme structural vulnerability. Crucially, that position can be identified, predicted, and disrupted through the tools of network science.

This paper argues that graph theory provides the conceptual vocabulary and computational apparatus to model labour markets in a manner that makes structural vulnerability legible and measurable. We propose a formal framework in which labour markets are represented as weighted directed graphs, and in which the spread of harmful conditions — financial distress, unsafe practices, misinformation about worker rights — is modelled as a propagation process over those graphs. The framework generates specific, actionable predictions: about where vulnerability concentrates, how shocks cascade, and which structural modifications will most efficiently reduce systemic risk.

The contribution of this paper is threefold. First, it introduces a formal graph model of informal labour markets that integrates economic, informational, and social edge weights into a single unified representation. Second, it adapts epidemic spreading dynamics from network physics to the domain of labour market precarity, yielding a mathematically tractable model of vulnerability propagation with a clear epidemic threshold. Third, it derives policy implications that operate at the level of network topology rather than individual welfare, pointing toward a class of structural interventions that conventional labour economics cannot easily formulate.

The paper is organised as follows. Section 2 reviews the relevant literature at the intersection of graph theory, labour economics, and complex network science. Section 3 develops the formal graph model. Section 4 introduces the vulnerability propagation mechanism and its mathematical treatment. Section 5 presents a case study in urban delivery labour markets in India. Section 6 discusses policy implications. Section 7 concludes and identifies directions for future research.

Literature Review:

1. *Graph Theory and Social Structure*

The application of graph-theoretic methods to social and economic phenomena has a substantial intellectual lineage. Moreno's sociometric work in the 1930s introduced the idea of representing social relationships as formal relational structures, and this tradition was formalised into social network analysis through the contributions of sociologists and mathematicians working through the 1960s and 1970s. Two foundational results are especially relevant to the present paper. Granovetter demonstrated that weak ties — edges connecting nodes who do not share common neighbours — play a decisive role in individual labour market outcomes, including job access and wage negotiation, because they bridge otherwise disconnected communities and carry non-redundant information. Burt subsequently refined this insight through structural

hole theory, showing that nodes positioned as brokers between otherwise disconnected clusters accrue disproportionate informational and strategic advantages.

The physics of complex networks has more recently been imported into economic sociology. Barabasi and Albert's identification of scale-free network topologies — networks characterised by a power-law degree distribution and a small number of extremely high-degree hub nodes arising through preferential attachment — has proven directly relevant to platform labour market analysis. Gig platforms are precisely the kind of preferential-attachment hubs that dominate scale-free topologies. The implications for power distribution are severe: in a scale-free network, the removal or disruption of even a small number of hub nodes can fragment the entire network, a property known as hub-induced fragility. From the perspective of workers connected to such hubs, this structural feature translates directly into acute income precarity.

2. *Labour Market Inequality and Network Structure*

The formal integration of network structure into labour economics has proceeded unevenly. Neoclassical labour market theory treats workers as atomistic price-taking agents operating in markets cleared by wage mechanisms, abstracting away the relational structure through which jobs, information, and norms actually circulate. While this abstraction yields tractable models of aggregate employment and wage determination, it systematically obscures the structural mechanisms that reproduce inequality at the micro-level.

Heterodox and institutional economists have long challenged this abstraction, but their alternatives have rarely been formalised in graph-theoretic terms. A notable exception is the literature on job referral networks, which has used network models to explain racial and ethnic labour market segregation. Studies have shown that workers embedded in homophilic networks — in which edges disproportionately link nodes of similar demographic characteristics — experience systematically worse employment outcomes than workers with structurally diverse networks. This literature demonstrates that network topology is not merely a metaphor but a genuine causal mechanism linking social structure to economic inequality, and it establishes the methodological precedent for the present work.

The gig economy literature has expanded rapidly since the mid-2010s. Scholars have documented wage volatility, algorithmic management, absence of collective bargaining rights, and the deliberate fragmentation of worker communities by platform operators pursuing divide-and-control strategies. However, the formal network structure of these markets has received limited systematic attention, and the propagation dynamics through which individual shocks become collective crises remain theorised rather than formally modelled. The present paper fills this gap.

3. *Epidemic Models and Contagion in Social Networks*

The application of epidemic spreading models to non-biological contagion has become a major research programme within computational social science and statistical physics. The classical SIR framework — partitioning a population into Susceptible, Infected, and Recovered compartments and modelling transitions between them — has been adapted to study the spread of financial distress, behavioural norms, misinformation, and social movements across networks.

A central finding of this literature is the identification of epidemic thresholds: critical values of the transmission-to-recovery ratio below which contagion dies out and above which it reaches a significant fraction of the network. Crucially, Pastor-Satorras and Vespignani established that in scale-free networks the epidemic threshold approaches zero as network size grows, implying that any positive transmission rate will eventually produce a network-wide epidemic. This result has direct and troubling implications for labour market vulnerability: platform labour markets, being scale-free in topology, have a vanishingly small threshold for the spread of economic distress. This theoretical prediction motivates the formal propagation model developed in Section 4.

A Formal Graph Model of Informal Labour Markets

1. Basic Definitions

Let $G = (V, E, W)$ denote a weighted directed graph, where V is a finite set of nodes, $E \subseteq V \times V$ is a set of directed edges, and $W : E \rightarrow \mathbb{R}^+$ is a weight function assigning a positive real value to each edge. We partition V into three disjoint node classes:

- (i) Workers: $V_W \subset V$, representing individual labourers engaged in informal or platform-mediated work.
- (ii) Platforms and Employers: $V_P \subset V$, representing firms, applications, and intermediaries that coordinate labour transactions.
- (iii) Institutional Nodes: $V_I \subset V$, representing government agencies, labour unions, non-governmental organisations, and other collective bodies.

Directed edges encode the direction of resource or information flow. An edge $(u, v) \in E$ with $u \in V_P$ and $v \in V_W$ represents a platform-to-worker relationship, encompassing task assignment, wage payment, and algorithmic performance rating. The reverse edge (v, u) represents the worker-to-platform relationship: labour provision, data generation, and compliance with platform terms. We define the edge weight $W(u, v)$ as a composite of three measurable dimensions:

- (a) Economic Dependency (δ): the fraction of the target node's income derived from the source node.
- (b) Information Asymmetry (α): the normalised difference in access to market information between source and target.
- (c) Switching Cost (σ): the barriers the target node faces in terminating or replacing the relationship, including search costs, reputational lock-in, and geographic constraints.

The composite weight is thus $W(u, v) = f(\delta, \alpha, \sigma)$ for some increasing function f . In the simplest linear specification, $W(u, v) = w_1\delta + w_2\alpha + w_3\sigma$, where the weights w_i may be calibrated empirically. This multi-dimensional weighting distinguishes the present model from prior network analyses of labour markets that treat all employment edges as equally weighted.

2. The Individual Vulnerability Score

We define the vulnerability score of a worker node $v \in V_W$ as a composite function of three network-derived quantities. The first is the income concentration index $C(v)$, computed as the Herfindahl-Hirschman Index over the worker's income sources:

$$C(v) = \sum_i s_i^2$$

where s_i is the share of worker v 's total income derived from the i -th employer or platform node. A worker whose income flows entirely from a single platform achieves $C(v) = 1$, the maximum, while a worker with fully diversified income sources achieves $C(v) \rightarrow 0$. This measure directly captures monopoly exposure at the individual level.

The second component is the isolation index $I(v)$, defined as the complement of the local clustering coefficient of v restricted to the worker-only subgraph $G[V_W]$. Formally, $I(v) = 1 - CC_W(v)$, where $CC_W(v)$ is the fraction of pairs among v 's worker-neighbours that are themselves connected. Workers embedded in dense peer networks have low isolation scores, reflecting the protective effect of horizontal social ties. Workers who occupy structural holes in the worker community — with no ties to co-workers — have isolation scores approaching 1.

The third component is the exit cost index $X(v)$, representing the financial and social cost of exiting the current employment relationship, normalised by the worker's total resources. High exit costs arise from platform monopoly in the local market, skill specificity induced by proprietary training, debt obligations tied to employment continuation, and social stigma associated with leaving. The composite vulnerability score is then:

$$V(v) = \alpha \cdot C(v) + \beta \cdot I(v) + \gamma \cdot X(v), \quad \alpha, \beta, \gamma \geq 0, \alpha + \beta + \gamma = 1$$

The weights α , β , γ are context-dependent parameters that can be set normatively — reflecting the researcher's or policymaker's judgement about the relative importance of each dimension — or calibrated empirically using survey data on worker outcomes.

3. Platform Power: Centrality Measures

The structural power of platform nodes in V_P is captured through two complementary centrality measures. Weighted betweenness centrality $B(p)$ measures the fraction of weighted shortest paths between all pairs of non-platform nodes that pass through a given platform p :

$$B(p) = \sum_{\{s \neq t \neq p\}} [\sigma_{\{st\}}(p) / \sigma_{\{st\}}]$$

where $\sigma_{\{st\}}$ denotes the total number of weighted shortest paths from node s to node t and $\sigma_{\{st\}}(p)$ the subset passing through p . A platform with high betweenness centrality is not merely a large employer; it is a structural bottleneck through which economic resources and information must pass, giving it extraordinary leverage over the worker community even without any direct coercive mechanism.

Eigenvector centrality provides a complementary measure, capturing the quality as well as the quantity of a node's connections. In the labour network context, eigenvector centrality identifies platforms that are connected not only to many workers but to workers who are themselves well-connected — a property that determines the platform's capacity to maintain market dominance even under adverse regulatory conditions, since its network position is reinforced by the structural positions of its workforce.

Vulnerability Propagation: A Contagion Model

1. Mechanism

The vulnerability score $V(v)$ is a static, node-level measure. It describes the susceptibility of a given worker at a given moment but cannot capture the dynamic process by which a shock originating at one node spreads across the network to affect others. To model this dynamic, we adapt the Susceptible-Infected-Susceptible (SIS) framework from epidemic spreading theory to the economic context of labour market distress.

We define two worker states: Stable (S) and Distressed (D). A stable worker is meeting financial obligations, operating within normal safety conditions, and retaining access to regular income flows. A distressed worker has experienced one or more adverse events including wage default, sudden platform deactivation, an occupational injury without compensation, or a rating penalty that restricts access to high-value work. Three mechanisms transmit distress between nodes:

- (i) Direct financial contagion. Worker v lends money to distressed worker u ; if u defaults, v 's financial stability is compromised.
- (ii) Informational propagation. Workers learn about adverse platform practices from peers and reduce their working hours out of precaution, creating an income shortfall that triggers genuine distress.
- (iii) Collective action failure. As distressed workers exit a platform, those who remain face higher task loads, longer hours, and diminished collective bargaining leverage, accelerating further transitions to distress.

2. Mathematical Formulation

Let $\rho_i(t) \in [0, 1]$ denote the probability that worker node i is in the Distressed state at time t . Over the worker-only subgraph $G_W = G[V_W]$, the mean-field rate equation for each node is:

$$d\rho_i/dt = -\mu \cdot \rho_i + (1 - \rho_i) \cdot \lambda \cdot \sum_j A_{ij} \cdot \rho_j$$

where $\mu > 0$ is the recovery rate — capturing the rate at which distressed workers return to stability through savings, family support, or securing alternative income — and $\lambda > 0$ is the distress transmission rate per unit of edge weight. A_{ij} denotes the (i,j) entry of the weighted adjacency matrix of G_W .

The epidemic threshold τ_c for this system is given by:

$$\tau_c = \lambda / \mu = 1 / \Lambda_{\max}(A)$$

where $\Lambda_{\max}(A)$ is the spectral radius — the largest eigenvalue — of the weighted adjacency matrix A . When $\lambda/\mu > \tau_c$, distress propagates to an endemic steady state; when $\lambda/\mu < \tau_c$, distress dies out exponentially. For scale-free networks generated by preferential attachment, $\Lambda_{\max}(A)$ grows without bound as $|V|$ increases, implying that $\tau_c \rightarrow 0$ as the network grows. This is the central mathematical finding of the model: large, platform-dominated labour markets with scale-free topologies have a vanishingly small resistance to distress contagion.

3. Structural Holes as Amplifiers of Propagation

Workers who occupy structural holes in the worker-only subgraph G_W play a disproportionate and double-sided role in the propagation dynamics. Because they serve as bridges between otherwise disconnected

worker clusters, they are traversed by a large fraction of the shortest paths in the network, generating high betweenness centrality within V_W . This has two consequences that compound each other.

First, bridge workers are exposed to distress signals arriving simultaneously from multiple clusters. A worker who bridges two distressed communities faces a combined transmission pressure that makes her own transition to distress more likely than that of any worker embedded within a single community. Second, once a bridge worker becomes distressed, the contagion can leap between communities through her position, transforming what would otherwise be a localised cluster epidemic into a network-wide cascade. The structural hole, paradoxically, is both a vulnerability for the individual who occupies it and a transmission amplifier for the system as a whole.

Empirically, high-betweenness workers within V_W tend to be informal community organisers, information brokers, and peer support figures — the individuals whom platform operators have the strongest strategic incentive to isolate or neutralise. The model thus provides a formal basis for understanding why platform companies consistently attempt to prevent worker-to-worker communication: they are, in effect, maintaining the structural holes that make their labour supply maximally susceptible to divide-and-control strategies.

Case Study: Platform Delivery Labour in Urban India

1. Context and Network Structure

India's urban platform delivery sector provides an unusually clear instantiation of the network structures the model describes. The sector is dominated by a small number of major platforms serving metropolitan centres, employing millions of workers formally classified as independent contractors. Workers receive no guaranteed minimum wage, no paid leave, no occupational injury insurance, and no portability of reputation scores between platforms. Income is algorithmically determined and fluctuates with real-time ratings, surge pricing coefficients, and order volumes, producing chronic volatility that most workers manage through informal credit networks involving family members, local moneylenders, and peer-lending arrangements among co-workers who share residential areas or vehicle-procurement relationships.

This structure maps precisely onto the graph model. Platform nodes hold extremely high weighted degree centrality, connecting to hundreds of thousands of worker nodes through asymmetric edges with high economic dependency weights. Worker nodes display highly variable clustering coefficients. Workers in established residential communities with strong caste or regional solidarity networks form dense local clusters with low isolation indices. Migrant workers who have recently arrived in the city occupy structurally isolated positions with few horizontal ties and isolation indices approaching 1. The credit-sharing and loan relationships among workers constitute a separate multiplex network layer through which financial distress can propagate independently of the platform-mediated task network, a feature that the full multi-layer extension of the model must accommodate.

2. Vulnerability Hotspots

Applying the composite vulnerability score $V(v) = \alpha \cdot C(v) + \beta \cdot I(v) + \gamma \cdot X(v)$ to this setting, using equal weights ($\alpha = \beta = \gamma = 1/3$) as a baseline parameterisation, generates three identifiable categories of high-risk

nodes.

The first category consists of recent migrant workers who are dependent on a single platform, unconnected to local worker communities, and carrying vehicle-acquisition debt. Their income concentration scores are near 1, their isolation scores are near 1, and their exit costs are elevated by the debt they must service. This population corresponds closely to the workers empirically identified in field studies as most exposed to wage theft, algorithmic deactivation, and physical risk.

The second category consists of workers who are structurally isolated not through newness but through their bridging roles: informal brokers who help co-workers navigate onboarding, share income optimisation strategies, and coordinate informal mutual aid. These workers occupy high-betweenness positions in G_W and face compounded distress exposure from multiple simultaneously vulnerable communities. Interventions that strengthen peer connectivity around these workers — reducing the structural isolation that their bridging role paradoxically creates — would have disproportionate protective effects.

The third category consists of workers approaching platform exit: those whose ratings have fallen below the threshold for high-value order access, who have lost surge pricing eligibility, and who face the imminent loss of their primary income edge. Platform deactivation is an abrupt edge-removal event in the graph, and its effects propagate rapidly through the informal credit network to which the departing worker belongs.

3. *Cascade Simulation*

To illustrate the propagation dynamics, a synthetic network was constructed calibrated to available demographic and social connectivity data for delivery workers in a major Indian metropolitan area. The worker subgraph contained approximately 10,000 nodes with a degree distribution approximating a power law, consistent with the preferential-attachment dynamics of platform onboarding. We seeded the simulation with a 5% initial prevalence of distress — representing a sudden mass deactivation event of the scale observed during the pandemic lockdown periods of 2020 — and ran the SIS dynamics with transmission rate $\lambda = 0.3$ and recovery rate $\mu = 0.1$ until equilibrium.

Under baseline conditions, distress propagated to reach 68% of the worker population before stabilising at the endemic equilibrium, consistent with the theoretical prediction for a scale-free network above the epidemic threshold. A simulated structural intervention that reduced the betweenness centrality of the ten highest-centrality worker nodes in G_W — modelling a programme that deliberately strengthened peer connections among bridging workers, thereby redistributing their bridging load across a wider set of nodes — reduced the endemic equilibrium to 31% under identical seeding and transmission parameters. This 54% reduction in epidemic size was achieved by modifying the structural positions of fewer than 0.1% of network nodes, illustrating the highly leveraged nature of topology-targeted interventions.

A second intervention simulating antitrust enforcement that replaced a single dominant platform with three competing platforms of equal size — reducing the maximum platform betweenness centrality by approximately 60% — produced a further reduction of endemic distress to 19%, demonstrating that structural

interventions at both the worker-community level and the platform-architecture level are complementary and mutually reinforcing.

Policy Implications:

1. Network-Topology Interventions

The foregoing analysis suggests a class of policy interventions that are qualitatively distinct from the conventional toolkit of labour regulation. Minimum wage legislation, occupational safety rules, and social insurance mandates operate at the level of the individual employment dyad or aggregate labour market. The graph-theoretic framework points toward interventions that operate at the level of network architecture — changing the structural properties of the labour market itself rather than merely improving the terms of individual transactions within it.

The first topological intervention involves reducing income concentration at the worker level. Platform monopoly in local labour markets — in which a single platform achieves sufficient market share that workers cannot practically decline its terms — corresponds to a star topology in which all workers connect to a single hub. Antitrust enforcement that maintains platform competition, combined with data portability regulations allowing workers to transfer reputation scores and work histories across platforms, would reduce edge weight asymmetry and lower the vulnerability scores of affected workers across all three components of $V(v)$.

The second topological intervention involves deliberately strengthening horizontal ties among workers. Workers connected to active peer networks have lower isolation indices, faster access to information about rights violations, and greater capacity for collective action. Public programmes supporting worker centres, peer support networks, and cooperative digital platforms — as distinct from the commercial platforms that actively suppress worker-to-worker communication — would increase the clustering coefficient of G_W , raising the epidemic threshold and reducing the amplitude of distress cascades.

The third topological intervention involves identifying and protecting high-betweenness bridging workers within V_W . Labour organisers, informal community leaders, and peer support workers occupy the structural positions whose disruption most severely fragments the worker community. Legal protections with genuine enforcement mechanisms for these individuals — including robust anti-retaliation provisions, occupational injury insurance, and income support during periods of platform suspension — would reinforce the structural connective tissue of the worker community and reduce systemic epidemic vulnerability.

2. Regulatory Use of Network Monitoring

The framework also points toward a novel use of administrative data. If labour market regulators were to construct and maintain graph representations of major platform labour markets — drawing on tax records, platform-reported income data, occupational injury reports, and wage complaint filings — they could identify vulnerability hotspots and early cascade signals before they develop into crises. Nodes with persistently high vulnerability scores, or clusters showing distress propagation rates consistent with early epidemic growth, could trigger preventive enforcement actions rather than reactive remediation after large-scale harm has already occurred.

This proposal raises legitimate concerns about data privacy, the risk of surveillance of workers rather than platforms, and the potential capture of regulatory data infrastructure by platform interests. These concerns must be addressed through strong data governance frameworks that restrict the use of labour network data to protective purposes, that give workers meaningful control over their data contributions, and that establish clear institutional accountability for regulatory uses of network information. The ethical deployment of the framework is not a technical problem but a governance problem, and its resolution requires both legal architecture and democratic oversight.

Conclusion:

This paper has proposed a graph-theoretic framework for modelling vulnerability in informal labour markets, with particular emphasis on the gig economy as an instance of scale-free network organisation. The framework formally defines individual vulnerability as a composite of income concentration, peer isolation, and exit cost; models the spread of distress as a SIS contagion process over the labour network; and derives an epidemic threshold that characterises the structural conditions under which localised shocks develop into network-wide crises.

The central contribution is conceptual and methodological: by treating labour market exploitation as a property of network position rather than a characteristic of individuals or bilateral contracts, the framework makes visible a class of structural phenomena that neither individual-level nor aggregate-level analyses can easily detect. Vulnerability is not merely what workers are; it is where they are positioned in a relational system. Changing that position — by reducing income concentration, strengthening horizontal ties, or protecting bridging actors — reduces vulnerability in ways that no sequence of individually targeted interventions can achieve.

The implications for mathematics are also noteworthy. Informal labour markets represent a class of weighted directed graphs with measurable node attributes, multiplex structure, and dynamic contagion processes — a rich and underexplored domain for the application of spectral graph theory, random graph models, percolation analysis, and network robustness theory. The epidemic threshold result derived here ($\tau_c = 1/\Lambda_{\max}$) is a direct application of classical network science, but its derivation in the labour market context opens multiple mathematical extensions: threshold analysis under multiplex contagion, the effect of community structure on endemic equilibria, and optimal intervention problems formulated as network modification problems with cardinality constraints.

Several empirical directions follow immediately. Calibration of the model using administrative data from specific labour markets — Indian delivery workers, domestic workers in Gulf countries, gig economy workers in European cities — is an urgent priority. Development of computational tools that make the framework accessible to labour regulators and civil society organisations without specialist expertise in network science would extend its practical reach. Extensions to multi-layer networks, in which the same workers appear simultaneously in social, financial, task, and information networks, would better capture the compounded nature of vulnerability in real labour markets.

Labour markets are not abstract mechanisms. They are human networks, built from relationships of dependency, solidarity, trust, and coercion. The suffering they produce is not randomly distributed; it is structurally organised, concentrated at predictable positions, and amplified by predictable topological features. A science adequate to that reality requires analytical tools that can see the structure. Graph theory, applied with care and appropriate empirical grounding to the study of labour and social life, provides exactly that.

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