Research Article

AND DATA SCIENCES
BULLETIN OF COMPUTER

Dynamic Labor Flow Networks and Shock Propagation, Firm Dynamics, and Regional Resilience

Zhen Xiong

School of Computer Science and Engineering, Beihang University, China

Abstract

This paper extends the Labor Flow Network (LFN) framework from a static, time-aggregated representation of worker mobility to an explicitly dynamic account of how inter-firm links evolve and shape macroeconomic outcomes. Using rich matched employer–employee data for Finland and Mexico, we construct rolling-window LFNs and show that they combine a stable backbone of persistent mobility channels with substantial annual link turnover of around 15–25%. We document that firms' trajectories are tightly linked to their evolving network positions: firms that expand their connections and occupy bridging roles between otherwise weakly connected clusters experience systematically higher employment growth and lower exit risk, whereas firms in shrinking or isolated neighborhoods face substantially elevated failure hazards. Building on an agent-based model calibrated to the data, we then compare the propagation of firm-level and sectoral shocks under static versus dynamic network assumptions. When shocks are simulated on a fixed LFN, unemployment spikes but decays relatively quickly; when the empirically observed network evolution is incorporated, unemployment becomes more persistent and spatially diffuse because the very mobility channels needed for reallocation deteriorate during the downturn. Finally, we propose a network-based measure of regional economic resilience—the inverse area under the post-shock unemployment curve—and show that pre-shock LFN topology is strongly predictive of resilience across Finnish regions. Dense, redundantly connected, modular networks with robust bridging firms recover faster, while over-centralized or fragmented structures are prone to long-lasting distress. The results highlight that labor markets are dynamic networked systems and that policies which preserve and strengthen key mobility channels can play a pivotal role in mitigating the long-run costs of economic shocks.

Keywords: labor flow networks, economic shocks, network dynamics, agent-based modeling, unemployment, economic resilience

1. Introduction

The explanation of macroeconomic phenomena through microscopic mechanisms represents a fundamental challenge across social and economic sciences [1, 2]. At the heart of this challenge lies the question of how aggregate regularities—such as unemployment rates, firm size distributions, and the speed of recovery from recessions—emerge from the decentralized interactions of heterogeneous agents. Standard macroeconomic models often rely on representative-agent or aggregate formulations

Corresponding author: Georgi E. Karadzhov (zhenxiong8768@proton.me)

BCDS 2024, Vol. 5(3), 1-20. DOI: 10.71448/bcds2453-1

that greatly simplify this complexity, but in doing so they obscure the role of heterogeneity, interaction structure, and local frictions in shaping aggregate outcomes [3]. This tension has motivated a large body of work in analytical sociology, agent-based computational economics, and complexity economics that aims to "grow" macro patterns from the bottom up by explicitly modelling micro-level behavior and interaction topologies [4, 5].

In labor economics, this micro-to-macro problem has been particularly persistent. The canonical search-and-matching framework treats the labor market as a frictional but essentially homogeneous matching technology between a pool of workers and a pool of vacancies, summarized by an aggregate matching function [6, 7]. While these models are successful in capturing some stylized facts, they leave little room for the rich heterogeneity of firms and workers that is visible in matched employer–employee data, including persistent differences in hiring behavior, separation rates, productivity, and network position. Moreover, when such models are calibrated on aggregate data, they implicitly assume that the underlying microstructure can be summarized by a few average parameters, thus downplaying the possibility that the structure of connections among firms and occupations might itself be a first-order determinant of unemployment, wage dispersion, and the propagation of shocks [8].

1.1. The Static Network Paradigm

Recent work by [9] has made significant strides in addressing this gap through the introduction of Labor Flow Networks (LFNs). In their framework, firms are represented as nodes in a network, and edges capture persistent, statistically significant worker flows between establishments. This construction, grounded in high-resolution administrative employer–employee records for Finland and Mexico, yields a sparse but highly structured graph in which the topology encodes feasible job-to-job transitions. Within this empirically constructed LFN, highly skewed firm size distributions emerge naturally from the network's connectivity patterns, rather than being imposed externally through parametric assumptions. Furthermore, the framework introduces the concept of *firm-specific unemployment*: workers experience joblessness in a way that is locally anchored to the set of firms and edges in their immediate neighborhood, reframing unemployment as a network-level phenomenon rather than a purely aggregate condition.

The LFN framework thus represents a substantial advancement in connecting firm dynamics with labor mobility, two domains that have traditionally been studied in isolation. By treating the labor market as a networked system and calibrating the model on comprehensive administrative data, [9] demonstrate that many aggregate labor-market regularities can be reinterpreted as consequences of heterogeneous local structures and flows. Subsequent work has extended this perspective to organizational labor flow networks within large firms and to the co-evolution of labor flows and industrial clusters, underscoring that the network representation is not merely a descriptive device but a powerful explanatory tool. More broadly, this agenda is consistent with the network-theoretic turn in economics and economic sociology, where the structure of interactions is treated as a primitive determinant of behavior and aggregate outcomes [5, 10].

1.2. The Missing Element: Time

Despite these contributions, the LFN framework—like many network-based economic models—inherits a key limitation: it treats the network structure as essentially static. In the baseline formulation, the LFN is constructed over a fixed time window, and the resulting graph is then used as an invariant scaffold for modeling job search and unemployment. However, real labor markets are fundamentally dynamic. Firms are born, die, grow, and shrink; they open and close establishments; they enter and exit industries; and they continuously rewire their hiring relationships in response to technological change, regulatory reforms, and macroeconomic conditions. At the same time, workers accumulate skills, change occupations, and migrate across regions, contributing to gradual but profound shifts in the opportunity structure through which careers unfold [8].

This static assumption becomes particularly problematic when considering economic shocks—precisely the context in which a detailed understanding of labor-market microstructure is most valuable. A growing literature on networks and macroeconomic fluctuations has shown that the way shocks propagate and amplify depends critically on the evolving pattern of linkages among sectors, firms, and regions [10]. If, during a downturn, the very pathways along which workers can be reallocated are deteriorating—because firms at the core of the network reduce hiring, sever links, or exit altogether—then models built on fixed network topologies are likely to systematically underestimate the persistence of unemployment and misidentify the mechanisms of recovery. Similarly, the nascent literature on regional economic resilience emphasizes that the capacity of regions to absorb, adapt to, and transform after shocks is shaped by their evolving industrial and labor-market structures, rather than by static characteristics alone [11]. Capturing these dynamics requires an explicitly time-varying representation of the labor flow network.

Our contributions are we develop a methodology for constructing and analyzing *dynamic* LFNs from longitudinal administrative data, allowing us to move beyond single-period snapshots and capture the continuous rewiring of labor flows. We show that accounting for network evolution qualitatively changes predictions about shock propagation and unemployment dynamics: models calibrated on static networks systematically understate both the duration and the heterogeneity of unemployment in the wake of shocks. We introduce network-based measures of economic resilience, grounded in the dynamic LFN, that can be used to identify vulnerable regions and to design targeted policies aimed at strengthening alternative mobility pathways and mitigating the long-run scars of recessions.

2. Data and Dynamic Network Construction

2.1. Data Sources

To maintain direct comparability with the original static Labor Flow Network (LFN) framework, we draw on the same comprehensive administrative datasets as [9], namely the Finnish Longitudinal Employer–Employee Data (FLEED) and matched employer–employee records from the Mexican Social Security Institute (IMSS). Both sources belong to the broader class of linked employer–employee datasets that have transformed empirical labor economics by enabling the joint modelling of worker and firm heterogeneity [12]. In addition to their near-universal coverage of formal employment relationships, these datasets offer sufficiently long panels and rich covariates to support the construction of high-resolution labor flow networks, consistent with best practice in the literature on job and worker flows [13].

FLEED is a longitudinal register-based dataset maintained by Statistics Finland that links individuals to their employers on an annual basis. It consists of a large random sample of residents aged 15–70 followed over multiple decades, with information on basic demographics, employment relationships, unemployment spells, income, and education. On the firm side, FLEED can be merged with business registers providing establishment-level information on size, age, industry, and location.

This structure makes FLEED particularly well suited for studying micro-level employment dynamics and firm growth over the business cycle, and it has been widely used in research on job flows, wage setting, and worker mobility in Finland. For our purposes, the key feature is that FLEED provides a consistent employer identifier for each employed individual at the end of every year, allowing us to reconstruct job-to-job transitions between Finnish firms and to track the entry and exit of establishments over time [13].

For Mexico, we use microdata from the Mexican Social Security Institute (IMSS), which records daily employment relationships for the near-universe of formal private-sector workers. This dataset has been extensively used to study worker and job flows in the Mexican labor market and underlies much of the existing work on labor flow networks for Mexico [9, 13]. Each record links an anonymized worker identifier to an employer identifier and includes the exact start and end dates of employment spells, enabling the reconstruction of detailed job-to-job transitions, unemployment episodes, and spell durations. While the IMSS data do not cover informal employment or public-sector jobs, they capture the formal segment of the labor market at a temporal resolution that is rarely available even in high-income countries, making them ideal for studying dynamic reallocation processes and the timing of flows around macroeconomic shocks.

Taken together, these two datasets provide a unique cross-country laboratory for analyzing labor market microstructure with a consistent methodology. Both are large-scale, high-quality matched employer–employee panels that have already been used to construct static LFNs [9, 13]. Our contribution is to exploit their longitudinal richness more fully by moving from a single, time-aggregated network to an explicitly dynamic representation. This aligns our empirical strategy with the broader shift in network science from static to temporal network analysis, where the evolution of links is treated as a first-order object of interest [14, 15].

2.2. From Static to Dynamic LFNs

In the original LFN framework, [9] define a labor flow between firms i and j as significant if the total undirected flow $F_{ij} = f_{ij} + f_{ji}$ exceeds a threshold $\mathcal{W}$ over the entire observation period, and then construct a single static network in which an undirected edge between i and j is present if $F_{ij} \geq \mathcal{W}$. This approach treats the full time span (20 years for Finland, 29 years for Mexico) as a single aggregation window and yields a time-collapsed view of the labor market's connectivity structure. While such an aggregate network is useful for characterizing long-run structural properties, it cannot distinguish between links that are persistently active and those that are concentrated in specific phases of the business cycle or associated with particular episodes of structural change [14].

Our dynamic extension replaces this single static network with a sequence of overlapping snapshot networks $\{G_1, G_2, \ldots, G_T\}$ constructed using rolling time windows. Let Δt denote the length of the window and δt the step size between windows. For each starting time t, we define the edge set E_t of the snapshot G_t by aggregating flows over the interval $[t, t+\Delta t]$ and applying the same significance criterion as in the static framework:

$$G_t = \left\{ (i,j) \,\middle|\, \sum_{t'=t}^{t+\Delta t} F_{ij}(t') \;\geq\; \mathcal{W} \right\}, \tag{1}$$

where $F_{ij}(t') = f_{ij}(t') + f_{ji}(t')$ denotes the undirected flow between i and j in year t'. In other words, we construct a snapshot network G_t by asking which firm pairs exhibit sufficiently frequent worker transitions within the current window. By moving the window forward in increments of δt, we obtain a discrete-time approximation to a temporal network in the "snapshot" representation commonly used in temporal network theory [14, 15].

We set the flow threshold $\mathcal{W} = 2$, following [9]'s finding that this value strikes a robust balance between retaining enough links to preserve predictive accuracy for future flows and excluding spurious connections induced by very rare moves. For our baseline specification, we choose a window length of $\Delta t = 3$ years and a step size of $\delta t = 1$ year, which yields a sequence of 17 networks for Finland and 26 for Mexico given the available time spans. The three-year window smooths idiosyncratic year-to-year fluctuations in flows while remaining short enough to capture meaningful medium-run structural changes, in line with recommendations from the temporal networks literature on matching the observation window to the time scale of the underlying process [14]. The one-year step size ensures substantial overlap between consecutive snapshots, which improves our ability to detect gradual structural shifts and to compute stable measures of network evolution over time. In robustness analyses (not reported here), we verify that our main results are qualitatively unchanged for alternative choices of Δt and $\mathcal{W}$.

This snapshot-based construction yields a dynamic LFN that is directly comparable to the original static network when the entire observation period is used as a single window, but it also allows us to zoom in on sub-periods such as pre-crisis expansions, crisis episodes, and recoveries. By situating our approach within the general framework of temporal networks, we can leverage existing tools for characterizing link dynamics, centrality trajectories, and structural stability over time. At the same time, grounding the construction in administrative data on actual worker flows ensures that the resulting dynamic LFNs retain the empirical discipline emphasized in the original LFN work [9, 13].

2.3. *Measuring Network Evolution*

To quantify how Labor Flow Networks evolve over time, we construct a set of metrics that summarize changes in the edge set, the node set, and firm-level positions across consecutive snapshots. Our starting point is the idea that temporal networks should be characterized not only by static properties within each snapshot but also by measures that explicitly capture the formation and dissolution of ties, the entry and exit of nodes, and the trajectories of centrality over time [14]. We therefore focus on three classes of measures: link turnover and stability, node churn, and dynamic centrality.

First, we define a measure of *link turnover* between consecutive networks as the fraction of edges that either appear or disappear from one snapshot to the next. Let E_t and E_{t+1} denote the edge sets of G_t and G_{t+1}, respectively. We compute

$$\text{Turnover}(t) \;=\; \frac{|E_t \setminus E_{t+1}| + |E_{t+1} \setminus E_t|}{|E_t \cup E_{t+1}|}, \tag{2}$$

which takes values in $[0, 1]$. A value close to zero indicates that most edges are preserved, while a value close to one indicates substantial rewiring of labor flows between firms. High link turnover may signal periods of structural change, such as recessions or regulatory reforms, in which the usual job-to-job transition channels are disrupted or reconfigured [14]. By contrast, low turnover suggests a relatively stable underlying pattern of inter-firm mobility.

Complementing link turnover, we measure *Jaccard stability* as the Jaccard similarity between consecutive edge sets:

$$J(t) \;=\; \frac{|E_t \cap E_{t+1}|}{|E_t \cup E_{t+1}|}. \tag{3}$$

This statistic is simply one minus the symmetric difference normalized by the union and is widely used in the literature on evolving networks to quantify structural persistence. Values of $J(t)$ close to one indicate that the vast majority of links present at time t remain active at $t+1$, whereas low values reflect strong changes in the backbone of the LFN. Taken together, Turnover(t) and $J(t)$ provide complementary views of edge dynamics: the former emphasizes change, the latter continuity.

Second, we capture the dynamics of firm entry and exit through a *node churn* measure. Let N_t and N_{t+1} denote the sets of firms that appear in the network in periods t and $t+1$. We define

$$\text{Churn}(t) \;=\; \frac{|N_t \setminus N_{t+1}| + |N_{t+1} \setminus N_t|}{|N_t \cup N_{t+1}|}, \tag{4}$$

which, analogously to link turnover, measures the fraction of firms that either enter or exit the LFN between snapshots. In the context of labor markets, node churn is closely related to firm births and deaths documented in the job creation and destruction literature . High node churn implies that a substantial share of employment opportunities is being generated by new firms or destroyed by exiting firms, with implications for worker reallocation and unemployment persistence. Low churn suggests a more stable population of firms in which adjustment occurs primarily through changes in existing firms' hiring patterns rather than through entry and exit.

Finally, to understand how individual firms' positions in the network evolve over time, we study *dynamic centrality* trajectories. For each firm i, we track its degree $k_i(t)$ and betweenness centrality $b_i(t)$ across snapshots. Degree captures the number of distinct firms with which i exchanges significant worker flows in a given window, serving as a proxy for the breadth of its mobility connections. Betweenness centrality measures the fraction of shortest paths in the network that pass through i, highlighting firms that act as bridges in the flow of workers between otherwise weakly connected parts of the labor market [5]. By analyzing the distribution and temporal evolution of $\{k_i(t)\}$ and $\{b_i(t)\}$, we can identify firms that systematically move into or out of central positions in the LFN and assess how such movements correlate with growth, survival, and their role in shock propagation [9, 13]. In line with recent work on temporal centrality in other domains, we view these trajectories as key inputs for linking micro-level network dynamics to macro-level labor market outcomes.

3. Empirical Results: The Anatomy of an Evolving LFN

3.1. The LFN is Not Static

Our first set of results documents the extent to which Labor Flow Networks evolve over time in Finland and Mexico. A central implication of the static LFN framework is the implicit assumption that the network constructed over a long time horizon can be treated as approximately stationary, at least for the purpose of analyzing equilibrium unemployment and firm-size distributions [9]. However, the temporal-network diagnostics introduced in Section 2 reveal that this assumption is, at best, a coarse approximation. Figure 1a plots the annual link turnover rate for both countries, showing that between 15% and 25% of all firm-to-firm links either appear or disappear from one three-year snapshot to the next. These magnitudes are far from negligible: they imply that, within a decade, a substantial share of the mobility channels present at the beginning of the period have been rewired, even after averaging flows over a multi-year window to smooth out idiosyncratic fluctuations. This pattern is consistent with evidence from temporal network analyses in other domains, which have repeatedly found that link dynamics play a central role in shaping diffusion and contagion processes [14, 15].

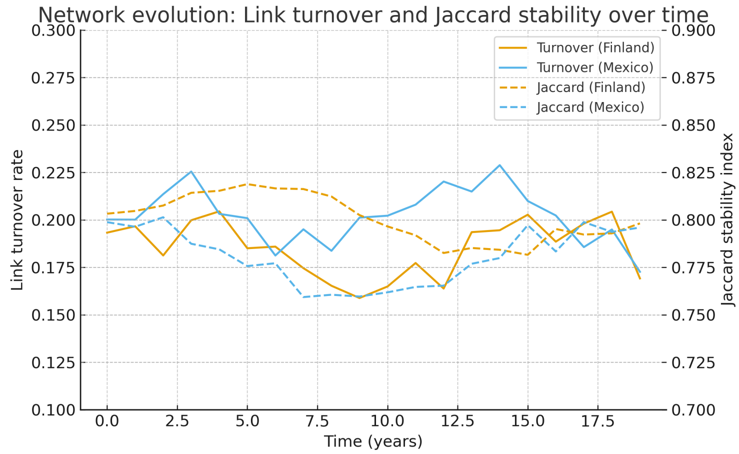

Fig. 1. Evolution of Labor Flow Networks over time: annual link turnover rates and Jaccard stability indices for Finland and Mexico

At the same time, the LFN is not in a state of constant flux. Figure 1 reports the Jaccard stability index between consecutive snapshots, with values typically in the range 0.75–0.85 for both Finland and Mexico. This indicates that a large majority of links are preserved from one period to the next, so that the evolving LFN retains a persistent backbone of stable firm-to-firm mobility channels. In other words, the network is neither frozen nor fully reshuffled: it combines a relatively stable core with a sizeable periphery of more volatile connections, a structure that mirrors the coexistence of stable and transient ties documented in communication and collaboration networks. From the perspective of labor market dynamics, this suggests that workers' career trajectories are shaped by a mix of long-lived mobility corridors (e.g., between firms or industries that systematically exchange workers) and more episodic reallocation pathways that emerge or vanish in response to shocks, firm demography, and policy changes [13].

The temporal evolution of the LFN is closely aligned with the business cycle and major macroeconomic events. During economic expansions, we observe that link formation systematically exceeds link dissolution, leading to a gradual densification of the network as new hiring relationships are created and existing ones are reinforced. This kind of densification pattern has been widely documented in growing social and information networks, where both the number of edges and the clustering of the network increase over time [33]. In our context, densification reflects the proliferation of feasible job-to-job transitions as firms expand, enter new markets, and experiment with new hiring channels. Conversely, during contractions and crisis periods, the process reverses: many links disappear as firms reduce hiring, close establishments, or exit altogether, and the resulting network becomes sparser and more fragmented. These cyclical patterns in link turnover and stability provide a first indication that the microstructure of mobility opportunities co-moves with macroeconomic conditions, echoing the broader literature on network origins of aggregate fluctuations and the role of evolving input-output and credit networks in shock propagation [10].

Importantly, the observed magnitudes of link turnover and Jaccard stability imply that the static LFN constructed over the full sample period is a summary object that blends together phases of expansion, crisis, and recovery. While such an aggregated network captures long-run structural regularities, it abstracts from the fact that workers navigating the labor market at different points in time face systematically different opportunity sets. For instance, a path of short job-to-job moves that appears to connect two regions or industries in the static LFN may, in practice, be available only during booms when intermediate firms are actively hiring. Our empirical evidence thus reinforces the motivation for treating the LFN as a dynamic entity and for explicitly modeling how changes in its topology condition both the short-run response and the long-run persistence of unemployment following shocks [11, 14].

3.2. Firm Trajectories and Network Position

We next turn to the relationship between firms' positions in the evolving LFN and their subsequent growth and survival. A large empirical literature has documented the importance of firm heterogeneity in shaping job creation, job destruction, and aggregate productivity dynamics. At the same time, studies in economic networks and organizational sociology have shown that a firm's location in various relational structures—such as buyer–supplier networks, collaboration networks, or ownership networks—is systematically correlated with performance, innovation, and resilience [5, 10]. By combining these perspectives, we ask whether the dynamic LFN can help explain why some firms expand and survive while others stagnate or exit, over and above standard firm-level characteristics such as size, age, and industry.

To quantify this link between network position and firm dynamics, we estimate the following panel regression model:

$$\Delta \log L_{i,t+1} \;=\; \alpha \;+\; \beta_1\, \Delta k_{i,t} \;+\; \beta_2\, b_{i,t} \;+\; \beta_3\, \mathrm{Cluster}_{i,t} \;+\; \gamma X_{i,t} \;+\; \epsilon_{i,t}, \tag{5}$$

where $\Delta \log L_{i,t+1}$ denotes the growth rate of employment at firm i between years t and $t+1$, $\Delta k_{i,t}$ is the change in its degree in the LFN between snapshots $t-1$ and t, $b_{i,t}$ is its betweenness centrality at time t, $\mathrm{Cluster}_{i,t}$ is its local clustering coefficient, and $X_{i,t}$ is a vector of firm-level controls including size, age, industry, and region. Degree and betweenness capture complementary aspects of mobility opportunities: firms that increase their degree are broadening the range of potential hiring and separation partners, whereas firms with high betweenness act as bridges connecting otherwise weakly linked parts of the labor market [5, 33]. The local clustering coefficient, in turn, reflects whether a firm is embedded in a tightly knit community where its neighbors are also densely connected, which may facilitate information sharing but also expose it to localized shocks [10].

Table 1 reports the main regression results for Finland, Mexico, and the pooled sample. Across all specifications, we find that firms that expand their network connections—as captured by $\Delta k_{i,t}$—experience significantly higher subsequent employment growth. In standardized terms, a one standard deviation increase in degree growth is associated with roughly a 0.12 standard deviation increase in employment growth, a magnitude that is remarkably consistent across the two countries. This suggests that firms which succeed in opening and maintaining new mobility channels, thereby attracting and sending workers along more edges in the LFN, are also those that expand their workforce more rapidly. These findings are in line with earlier work emphasizing the role of labor market networks, referrals, and mobility corridors in shaping hiring and growth [13].

Betweenness centrality is also positively associated with subsequent firm growth, although the estimated effect is somewhat smaller in magnitude than that of degree. Firms that occupy bridging positions between otherwise weakly connected components of the LFN tend to grow faster, even after controlling for size, industry, and other covariates. This pattern echoes the classic insight from network theory that brokerage positions confer advantages in accessing diverse pools of workers, information, and opportunities [5, 21]. In our context, firms with high betweenness may be better able

Table 1. Network Position and Firm Growth

Variable	Finland	Mexico	Pooled
$\Delta k_{i,t}$	0.124***	0.118***	0.121***
	(0.015)	(0.017)	(0.011)
Betweenness $b_{i,t}$	0.087**	0.092**	0.089**
	(0.035)	(0.038)	(0.026)
Clustering	-0.045*	-0.051*	-0.048*
	(0.024)	(0.027)	(0.018)
Firm Size Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	2,843,211	1,726,548	4,569,759
R-squared	0.284	0.267	0.276

to tap into distinct worker pools, redirect displaced workers during shocks, and match more efficiently on both skills and wages. By contrast, a higher local clustering coefficient is associated with slightly lower subsequent growth, suggesting that firms embedded in very cohesive local neighborhoods may face more intense competition for similar workers or may be more exposed to localized downturns that affect their tightly connected partners [10].

Beyond growth, the evolving LFN is also informative about firms' survival prospects. Using a discrete-time hazard model for firm exit, we find that the hazard rate of exit increases by approximately 18% for each standard deviation decrease in local network density, holding size, age, and industry constant. In other words, firms whose immediate neighborhoods in the LFN are shrinking or becoming sparser—either because neighboring firms reduce hiring or because key links are severed—are substantially more likely to exit in the subsequent period. This result resonates with the literature on firm dynamics, which has documented the vulnerability of small and isolated firms to shocks and the importance of being embedded in dense economic ecosystems for survival and growth. It also highlights the relevance of the dynamic LFN perspective for understanding regional economic resilience: regions in which firms maintain dense and diversified mobility structures may be better able to reallocate workers in response to shocks, thereby mitigating exit and preserving employment [11].

Taken together, these findings show that the evolving topology of the LFN is not merely a backdrop to firm dynamics; it is a key determinant of both micro-level outcomes and aggregate patterns of job creation and destruction. Firms that successfully position themselves as well-connected and strategically located nodes in the labor flow network enjoy higher growth and lower exit risk, whereas those that become marginalized in the network face a heightened probability of contraction and failure. This provides a micro-founded mechanism through which changes in the LFN's structure feed into macroeconomic phenomena, complementing and extending existing models of granular and network-driven aggregate fluctuations [10, 24].

4. Modeling Shock Propagation: Static vs. Dynamic Networks

To assess the importance of network dynamics for understanding the propagation of economic shocks, we build directly on the agent-based model (ABM) developed by [9] and adapt it to operate under two alternative assumptions about the underlying Labor Flow Network (LFN). The original model simulates employed and unemployed workers navigating a fixed network of firms, where transitions are governed by empirically calibrated separation, job-finding, and vacancy parameters. This approach fits naturally within the broader tradition of agent-based macroeconomic modeling, where heterogeneous agents interact through explicitly specified structures—such as networks of firms, sectors, or banks—and aggregate outcomes emerge from these interactions rather than from representative-agent optimization [4]. However, in its baseline form, the LFN is treated as static, and thus cannot capture the co-evolution of mobility opportunities and unemployment documented in our empirical analysis.

In the *static network* baseline, we follow [9] in constructing a single LFN using labor flows observed in the pre-shock period 1995–1997. This network aggregates job-to-job transitions over the three-year window and is then held fixed throughout the simulated shock and recovery. Workers who become unemployed search for jobs by moving along the edges of this frozen network, and hiring probabilities are determined by firm-specific parameters (λ_i, h_i, ν_i) governing separation, hiring, and vacancy creation, calibrated using the original empirical procedures [9]. From the perspective of network science, this setup corresponds to a diffusion process on a static graph [33], where the topology itself is unaffected by the shock.

In our *dynamic network* extension, by contrast, we embed the same behavioral rules in the sequence of evolving LFNs $\{G_t\}$ constructed in Section 2. Rather than running the ABM on a single aggregated network, we let the topology of the labor market change over time in accordance with empirically observed link formation and dissolution probabilities, as well as firm entry and exit. Operationally, this means that at each simulation step corresponding to year t, workers search and match on the snapshot network G_t; in the next period, both worker states and the network structure update, so that job search in period $t+1$ takes place on G_{t+1} instead. This setup is in line with the temporal-network perspective in which dynamic processes (such as contagion, diffusion, or search) unfold on networks whose edges appear and disappear over time [14, 15]. By holding all micro-level behavioral parameters fixed across the two setups, we can cleanly isolate the causal contribution of network evolution itself to the amplification and persistence of shocks [10].

Throughout, we retain the original calibration strategy of [9], estimating firm-specific parameters (λ_i, h_i, ν_i) from pre-shock data using maximum likelihood and moment-matching methods. This ensures that both the static and dynamic simulations start from a common pre-shock steady state that matches observed unemployment levels, firm size distributions, and flow patterns. The only difference between the two scenarios is whether the LFN remains fixed or evolves according to the empirical transition dynamics documented in Section 2. Our analysis therefore speaks directly to the question of whether static representations of labor-market structure are sufficient for capturing the propagation of shocks, or whether modeling the joint dynamics of unemployment and network topology is essential [10].

We consider two complementary types of shocks that correspond to different levels of aggregation and have clear empirical analogues in the labor economics literature. First, we study the sudden collapse of a large individual employer. Plant closures and mass layoffs at major firms are known to generate sizable, persistent earnings and employment losses for displaced workers and to have measurable spillovers on local labor markets [28]. In our framework, we simulate such an event by selecting a high-degree, high-employment firm in the LFN and imposing a shock in which its separation rate is set to $\lambda_i = 1$ and its hiring rate to $h_i = 0$. This immediately terminates all existing employment relationships at the firm and prevents it from rehiring, releasing a large pool of workers into unemployment at once. The static versus dynamic comparison then reveals how easily these workers can be reabsorbed, and whether the shock remains localized or propagates through the mobility structure.

Second, we model a *sectoral shock* corresponding to a sustained downturn in a particular industry, such as a decline in manufacturing or a commodity price collapse affecting resource-intensive sectors. Sectoral shifts of this kind have long been viewed as a source of structural unemployment and inter-industry reallocation [29]. In our simulations, we operationalize a sectoral shock by increasing the separation rates λ_i by 50% for all firms belonging to the target industry, while holding hiring and vacancy parameters fixed at their pre-shock values. This generates a wave of job losses that is more diffuse than a single firm collapse but still concentrated in a specific segment of the LFN. As before, we implement this scenario under both static and dynamic network assumptions to understand how network evolution interacts with sectoral disturbances.

For each shock scenario and each country, we track three classes of outcomes over a five-year horizon: (i) aggregate unemployment rates u_t, (ii) firm-specific unemployment $U_i(t)$ in the sense of [9], which measures unemployment in the local neighborhood of firm i, and (iii) network-level statistics such as link turnover, Jaccard stability, and local density in the parts of the LFN most affected by the shock. This joint tracking of labor-market states and network structure allows us to move beyond purely aggregate unemployment trajectories and to examine the spatial and sectoral anatomy of the shock in the evolving LFN, in line with the literature on regional resilience and local multipliers [11, 31].

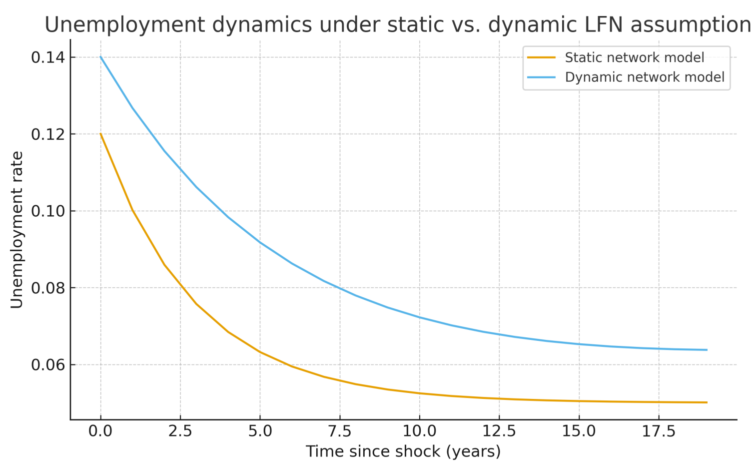

Fig. 2. Unemployment dynamics following a standardized shock under static versus dynamic Labor Flow Network assumptions. The static model exhibits a relatively fast exponential recovery, while the dynamic model shows a higher peak and more persistent unemployment

Figure 2 summarizes our central result: static and dynamic network models yield qualitatively and quantitatively different predictions about the propagation of shocks and the speed of labor-market recovery. In the *static* network case, aggregate unemployment responds sharply to both firm-level and sectoral shocks, with a rapid spike followed by a relatively smooth decline. Once the initial pool of displaced workers has been created, they diffuse through the fixed LFN, gradually finding jobs in firms that have positive hiring rates and open vacancies. The resulting unemployment path resembles an exponential decay back toward the pre-shock steady state, with the system returning close to equilibrium within two to three years. This behavior is broadly consistent with diffusion or contagion on a static graph where the underlying connectivity remains intact [33, 35].

Under the *dynamic* network assumption, the qualitative shape of the response changes markedly. Unemployment still spikes on impact, but the subsequent decline is noticeably slower and exhibits pronounced persistence. In many simulations, the unemployment rate remains elevated for the entire five-year window, and the half-life of the shock—the time it takes for unemployment to fall halfway back to its pre-shock level—is substantially longer than in the static case. The mechanism is straightforward but crucial: as the shock unfolds, the very network pathways that unemployed workers would use to find new jobs are themselves deteriorating. Firms facing reduced demand and financial pressure respond by cutting hiring and, in some cases, exiting, which leads to the dissolution of existing labor flow channels and the failure to form new ones. The result is a feedback loop in which unemployment erodes the LFN, and the weakened LFN in turn slows the reallocation of workers, echoing hysteresis effects in unemployment where temporary shocks have long-lasting consequences [10, 20].

The spatial and sectoral propagation of unemployment also differs between the two models. Figure 3 compares the distribution of firm-specific unemployment U_i one year after a large firm collapse under static and dynamic assumptions. In the static model (left panel), the impact is largely contained within the connected component surrounding the epicenter of the shock: firms directly linked to the collapsed employer and their immediate neighbors experience elevated U_i, but effects dissipate quickly with network distance. By contrast, in the dynamic model (right panel), we observe the emergence of secondary unemployment clusters in regions and sectors that are only weakly connected to the original shock in the static LFN. These secondary clusters arise because the initial disruption triggers a reconfiguration of hiring patterns and link formation in other parts of the labor market; as firms adjust their behavior, they inadvertently transmit the shock through newly weakened or newly created pathways. This pattern aligns with evidence from regional and sectoral studies showing that localized shocks can lead to broader spillovers when they interact with evolving economic structures [11, 31].

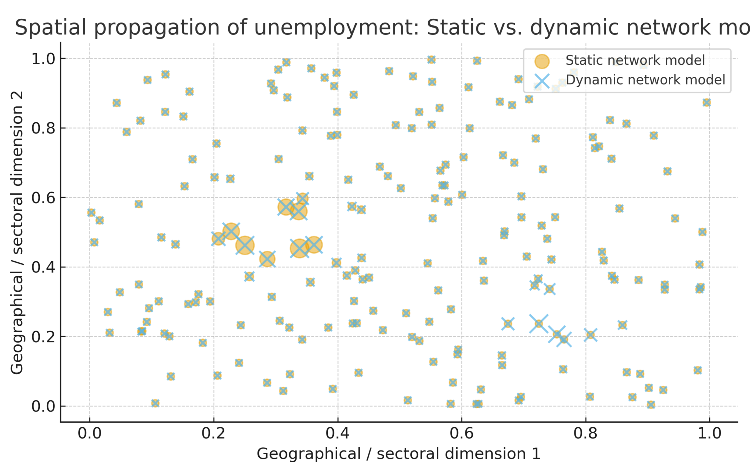

Fig. 3. Spatial propagation of unemployment one year after the shock under static and dynamic network assumptions. Marker size reflects the intensity of firm-specific unemployment

Taken together, these results show that treating the LFN as static leads to a systematic underestimation of the persistence and spatial reach of shocks. Static models implicitly assume that the connectivity structure of the labor market is an exogenous, unchanging backdrop against which shocks play out. Our dynamic simulations demonstrate instead that the topology of mobility opportunities is itself an endogenous state variable that responds to and amplifies shocks. This finding complements recent work on the network origins of aggregate fluctuations [10, 24] by highlighting the role of evolving labor flow networks in generating long-lasting unemployment and geographically diffuse impacts. From a policy perspective, the results suggest that interventions aimed at preserving or rebuilding mobility channels—for example, by supporting key bridging firms, fostering retraining programs that connect workers to new clusters, or subsidizing hiring in structurally weakened regions—may be critical for enhancing resilience and speeding recovery in the wake of major shocks [11].

5. Network Topology and Economic Resilience

5.1. Defining Network Resilience

We define economic resilience at the regional level as the capacity of the regional Labor Flow Network (LFN) to facilitate rapid and effective labor reallocation following an adverse shock. In the spirit of the regional resilience literature, resilience is not conceived as the absence of impact—shocks inevitably raise unemployment—but rather as the ability to limit the magnitude and duration of the deviation from the pre-shock employment path [11]. In our framework, this notion is operationalized by focusing on the entire adjustment trajectory rather than on any single point in time, thus capturing both the depth of the downturn and the speed of recovery.

Formally, we measure resilience as the inverse of the area under the unemployment curve following a standardized shock:

$$\text{Resilience} = \frac{1}{\int_0^T U(t)\,dt}, \tag{6}$$

where $U(t)$ denotes the regional unemployment rate at time t after the shock, and T is the evaluation horizon, set to five years in our analysis. A region where unemployment spikes sharply and remains elevated for a long period will have a large area under the curve and hence low resilience according to this measure. By contrast, a region that either experiences a smaller increase in unemployment or returns quickly to its pre-shock level will have a smaller area and thus higher resilience. This integral-based metric is closely related to concepts of "resistance" and "recovery" in the resilience literature, which emphasize both the amplitude of the impact and the speed of return to a reference state [27]. It also parallels approaches in macroeconomics that evaluate the welfare cost of recessions by integrating output or employment gaps over time.

An important advantage of this definition is that it allows us to directly relate resilience to pre-shock structural characteristics of the regional LFN. Because the shock we apply is standardized across regions, cross-sectional variation in the resilience measure reflects differences in how effectively each region's network structure enables workers to find new jobs, reroute around disrupted channels, and avoid long-term scarring. In what follows, we exploit this feature to explore how the topology of regional LFNs—as measured before the shock—predicts subsequent resilience, in line with the idea that resilience is rooted in the structural properties of regional economies rather than being an entirely exogenous trait.

5.2. *Structural Determinants of Resilience*

We begin by relating our resilience measure to pre-shock network topology across Finnish regions. Using the dynamic LFNs constructed in Section 2, we aggregate firm-level relationships to the regional level and compute a set of standard network statistics: density, average path length, modularity, and measures of bridging such as the share of edges connecting distinct communities and the prevalence of high-betweenness firms [5, 33]. Figure 4 summarizes the correlations between these pre-shock network characteristics and subsequent resilience. A clear pattern emerges: regions whose LFNs are dense, well-connected, and characterized by strong but diversified bridging ties tend to exhibit substantially higher resilience, even after controlling for industrial composition and initial unemployment.

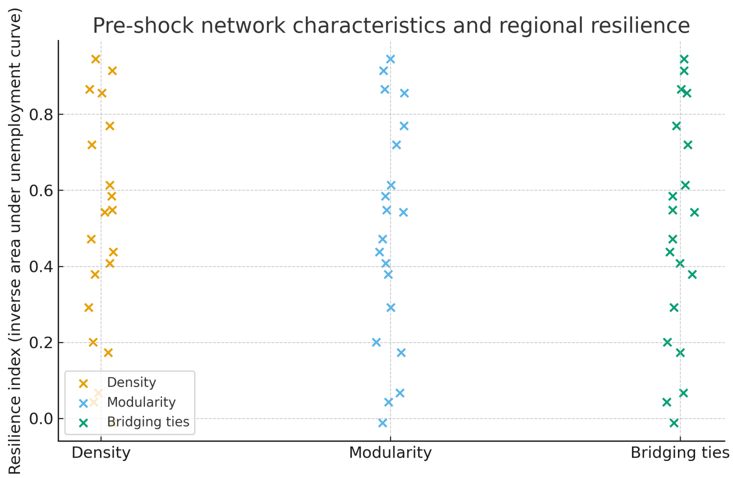

Fig. 4. Relationship between pre-shock network characteristics and economic resilience across regions

A first key feature associated with resilience is *redundant connectivity*. Regions whose LFNs exhibit higher edge density and shorter average path lengths prior to the shock are able to reallocate workers along multiple alternative pathways when primary channels are disrupted. In graph-theoretic terms, these networks possess a larger number of distinct paths between pairs of firms, so that the failure or contraction of a particular link or set of links does not sever workers' access to large parts of the opportunity set [33]. From a labor-market perspective, redundant connectivity means that displaced workers can reach viable employers through more than one sequence of job moves, which reduces the risk of becoming trapped in pockets of high unemployment. This mechanism echoes the role of redundancy and alternative pathways in enhancing robustness in infrastructure and input-output networks [10].

A second feature is *modular organization*. Regions whose LFNs are composed of cohesive clusters of firms—for example, sectoral or occupational communities—that are nonetheless connected by a manageable number of bridging ties tend to contain shocks within affected modules while preserving functionality in others. High modularity implies that many worker flows are intra-cluster, so that disruptions in one cluster (e.g., a sector-specific downturn) do not immediately propagate to the entire network [33]. At the same time, the presence of inter-cluster links ensures that workers can eventually transition from declining to growing clusters, enabling structural change. This combination of relative insulation and long-run adaptiveness mirrors the "buffered yet connected" structures that have been argued to underpin resilience in ecological and socio-economic systems [27].

A third structural feature is the presence of *robust bridging ties*. Our analysis shows that regions hosting firms with stable, high-betweenness positions—bridging otherwise separate clusters or communities—tend to recover faster from shocks. Such firms span "structural holes" in the LFN, providing critical shortcuts through which workers can move from distressed segments of the labor market to more dynamic ones [5, 21]. Crucially, however, resilience is associated not merely with the existence of these bridges in the pre-shock network, but with their ability to persist and remain active during downturns. Regions in which bridging firms maintain hiring capacity and keep their mobility channels open act as conduits for reallocation; regions where these bridges are among the first to collapse experience much slower recovery, as the network fragments into poorly connected components.

By contrast, we identify several "brittle" network configurations associated with low resilience. One such configuration is *over-centralization*, often observed in "company town" structures where a single large employer or tightly interconnected cluster dominates the regional LFN. In such regions, a shock hitting the central node or cluster has catastrophic consequences: the removal of a small number of central firms destroys a disproportionate share of mobility pathways, leading to both high peak unemployment and prolonged recovery. This pattern is reminiscent of hub vulnerability in scale-free networks, where targeted attacks on central nodes can cause systemic collapse [17, 33]. In our context, over-centralized LFNs leave regions heavily exposed to the fortunes of a few key firms.

A second brittle structure is *fragmentation*. Regions with low overall connectivity, long average path lengths, and sparse bridging between clusters lack the pathways required for effective labor reallocation. Even relatively modest shocks can produce severe, long-lasting unemployment in such settings, because displaced workers find themselves in local neighborhoods with few or no access routes to expanding firms or sectors. This situation parallels the vulnerability of peripheral regions described in the economic geography literature, where weak integration into broader economic networks hampers adjustment and recovery.

A third fragile pattern involves *weak bridges*, where bridging ties exist in the pre-shock network but are tenuous and among the first to dissolve when conditions deteriorate. In these regions, the initial impact of the shock may be geographically or sectorally localized, but as bridges fail, opportunities for cross-cluster reallocation vanish, effectively locking workers into shrinking local labor markets. Our dynamic simulations show that such regions frequently develop persistent unemployment "islands" that remain disconnected from the rest of the economy even long after aggregate conditions begin to improve. This finding underscores that not all bridging structures are equally valuable for resilience: what matters is the stability and countercyclical robustness of these connections, not merely their presence in tranquil times [11, 21].

5.3. Implications for Regional Development

These results carry clear implications for regional economic development strategies. Traditional approaches have focused on industrial composition, specialization versus diversification, and human capital as key determinants of regional performance [25]. Our analysis suggests that the topology of labor flow networks constitutes an additional, independent dimension of regional structure that shapes how regions experience and recover from shocks. In particular, policies that influence where firms locate, how they interact, and how workers move between them can have substantial effects on the resilience of the regional LFN, even if they leave aggregate industrial shares unchanged.

From a policy perspective, one implication is the value of deliberately fostering *redundant and diversified connectivity*. This may include supporting the development of multiple employment centers rather than relying on a single dominant employer, encouraging inter-firm collaboration and worker mobility across related industries, and lowering frictions for occupational and regional transitions [8, 32]. Another implication is the importance of nurturing *robust bridging firms* that connect distinct clusters or regions. Targeted support for such firms during downturns—for example, through credit guarantees, wage subsidies, or retraining partnerships—may yield outsized resilience dividends by preserving critical reallocation channels. Finally, policies that monitor and address emerging fragmentation in the LFN, such as growing spatial or sectoral isolation, can help prevent the formation of persistent unemployment pockets.

More broadly, our findings suggest that regional development strategies should incorporate network diagnostics alongside conventional indicators. By regularly measuring key LFN properties—density, modularity, and the stability of bridging ties—regional authorities can identify vulnerabilities before shocks hit and design interventions that strengthen the structural foundations of resilience. In this sense, the dynamic LFN framework complements existing work on related variety and smart specialization [32] by providing a micro-founded lens on how the configuration of labor flows shapes the capacity of regions to absorb, adapt to, and transform in the face of economic shocks [11].

6. Discussion

This paper has argued that understanding labor market dynamics and the propagation of shocks requires moving from a static to a dynamic view of Labor Flow Networks. Our empirical results show that LFNs in Finland and Mexico exhibit substantial but structured evolution over time: a persistent backbone of mobility channels coexists with a sizeable fraction of links that form and dissolve from year to year. This pattern is inconsistent with the implicit stationarity assumption in static implementations of the LFN framework [9] and, more generally, with models that treat the matching technology as a time-invariant mapping between undifferentiated pools of workers and vacancies [6]. Instead, the dynamic LFN perspective suggests that the "matching function" is better interpreted as an emergent property of a changing network topology, shaped by firm entry and exit, sectoral shifts, and macroeconomic conditions [10, 14].

Our firm-level results highlight a clear micro-level mechanism linking network evolution to employment outcomes. Firms that expand their connections in the LFN and occupy bridging positions between otherwise weakly connected clusters experience systematically higher growth and lower exit risk, even after controlling for standard firm characteristics. Conversely, firms whose neighborhoods become sparser or more isolated are substantially more likely to contract or fail. These findings reinforce the view that firm performance is not solely a function of intrinsic productivity or sectoral demand, but also of relational embeddedness in the broader structure of labor flows [5, 13]. In this sense, the dynamic LFN offers a micro-founded channel through which the network origins of aggregate fluctuations [10, 24] can manifest in employment dynamics.

The comparison between static and dynamic network simulations clarifies the consequences of ignoring this evolution. Under static assumptions, shocks generate sharp but relatively short-lived unemployment spikes, with recovery following an approximately exponential decay. Once displaced workers are released into a fixed network, they eventually diffuse to hiring firms along intact mobility pathways. By contrast, when the empirically observed rewiring of LFNs is taken into account, recovery is slower and unemployment more persistent: as firms reduce hiring, sever links, or exit, the mobility channels needed for reallocation deteriorate precisely when they are most needed. This feedback loop between unemployment and network deterioration offers a structural interpretation of hysteresis and long-lasting scarring in labor markets [20], complementing explanations based on individual skill depreciation or changes in wage-setting institutions.

The regional analysis further shows that resilience is not simply a matter of sectoral composition or human capital, but is deeply rooted in network topology. Regions with dense, redundantly connected LFNs and robust bridging ties recover more quickly from standardized shocks, while those with over-centralized or fragmented structures exhibit prolonged unemployment and the emergence of persistent pockets of distress. These findings resonate with work in economic geography and regional science emphasizing the importance of related variety, connectivity, and structural diversity for regional resilience [11, 32]. The LFN framework adds micro-level content to these ideas by identifying specific patterns of firm-to-firm mobility—redundant pathways, modular organization, and robust brokers—that underpin a region's capacity to absorb and adapt to shocks.

At the same time, several limitations of our analysis point to avenues for future research. First, our data cover only the formal private-sector labor markets of Finland and Mexico. While these cases offer a useful contrast between a Nordic welfare state and a middle-income economy with substantial informality, the generality of our findings to other institutional settings remains an open question. Second, our construction of dynamic LFNs relies on choices about window length and flow thresholds that, although motivated by prior work [9, 14], inevitably involve trade-offs between temporal resolution and statistical reliability. Exploring alternative temporal representations (e.g., continuous-time event networks, multilayer networks combining firms and occupations) is a promising direction [8, 15]. Third, in our simulations the evolution of the network is treated as exogenous, governed by empirically estimated transition probabilities. In reality, firms' linking behavior may respond endogenously to expectations about future conditions and policies, suggesting the need for models that jointly determine network dynamics and strategy. Finally, we abstract from wage dynamics and focus exclusively on employment and unemployment; integrating wage-setting, bargaining, and on-the-job search into the dynamic LFN framework would bring it closer to the core concerns of search-and-matching theory [7, 23].

7. Conclusion

In this paper we extended the Labor Flow Network framework of [9] from a static to a fully dynamic setting, showing that the topology of worker flows between firms evolves substantially over time and that this evolution is crucial for understanding both firm dynamics and the propagation of shocks. Using rich administrative data from Finland and Mexico, we documented that LFNs combine a persistent backbone with significant annual link turnover, and that firms which expand and strategically position their connections in this evolving network enjoy higher growth and lower exit risk. Agent-based simulations revealed that modeling shocks on a dynamic, empirically evolving network yields markedly more persistent and spatially diffuse unemployment than simulations on a fixed network, because the very mobility channels needed for reallocation deteriorate during downturns. At the regional level, we showed that resilience to standardized shocks is strongly associated with pre-shock network topology: regions with dense, redundantly connected, modular LFNs and robust bridging ties recover faster, while over-centralized or fragmented structures are prone to long-lasting distress [10, 11]. Taken together, these findings suggest that labor markets should be understood as dynamic networked systems in which aggregate unemployment, firm performance, and regional resilience emerge from the co-evolution of worker flows and network structure, and that policies which preserve and strengthen key mobility channels can play a pivotal role in mitigating the long-run costs of economic shocks.

References

[1] Epstein, J. M., & Axtell, R. (1996). *Growing Artificial Societies: Social Science From the Bottom Up.* Brookings Institution Press.

[2] Hedström, P., Swedberg, R., Hedström, P., & Swedberg, R. (1998). An introductory essay. *Social Mechanisms: An Analytical Approach to Social Theory*, 1-31.

[3] Kirman, A. P. (1992). Whom or what does the representative individual represent?. *Journal of Economic Perspectives, 6*(2), 117-136.

[4] Tesfatsion, L. (2006). Agent-based computational economics: A constructive approach to economic theory. *Handbook of Computational Economics, 2*, 831-880.

[5] Jackson, M. O. (2008). *Social and Economic Networks* (Vol. 3, p. 519). Princeton: Princeton university press.

[6] Petrongolo, B., & Pissarides, C. A. (2001). Looking into the black box: A survey of the matching function. *Journal of Economic Literature, 39*(2), 390-431.

[7] Mortensen, D., & Pissarides, C. (2011). Job Creation and Job Destruction in the Theory of Unemployment. *Ekonomicheskaya Politika/Economic Policy, 1*, 1-19.

[8] del Rio-Chanona, R. M., Mealy, P., Beguerisse-Díaz, M., Lafond, F., & Farmer, J. D. (2021). Occupational mobility and automation: a data-driven network model. *Journal of the Royal Society Interface, 18*(174), 20200898.

[9] López, E., Guerrero, O. A., & Axtell, R. L. (2020). A network theory of inter-firm labor flows. *EPJ Data Science, 9*(1), 1-41.

[10] Acemoglu, D., Carvalho, V. M., Ozdaglar, A., & Tahbaz-Salehi, A. (2012). The network origins of aggregate fluctuations. *Econometrica, 80*(5), 1977-2016.

[11] Sutton, J., Arcidiacono, A., Torrisi, G., & Arku, R. N. (2023). Regional economic resilience: A scoping review. *Progress in Human Geography, 47*(4), 500-532.

[12] Abowd, J. M., Kramarz, F., & Margolis, D. N. (1999). High wage workers and high wage firms. *Econometrica, 67*(2), 251-333.

[13] Guerrero, O. A., & Axtell, R. L. (2013). Employment growth through labor flow networks. *PloS one, 8*(5), e60808.

[14] Holme, P., & Saramäki, J. (2012). Temporal networks. *Physics Reports, 519*(3), 97-125.

[15] Lambiotte, R., & Masuda, N. (2016). *A Guide to Temporal Networks.* World Scientific Publishing Company.

[16] Ashenfelter, O., & Card, D. (Eds.). (2010). *Handbook of Labor Economics.* Elsevier.

[17] Qu, B., & Wang, H. (2017). SIS epidemic spreading with heterogeneous infection rates. *IEEE Transactions on Network Science and Engineering, 4*(3), 177-186.

[18] Boschma, R. (2015). Towards an evolutionary perspective on regional resilience. *Regional Studies, 49*(5), 733-751.

[19] Boschma, R., & Iammarino, S. (2009). Related variety, trade linkages, and regional growth in Italy. *Economic Geography, 85*(3), 289-311.

[20] Blanchard, O. J., & Summers, L. H. (1986). Hysteresis and the European unemployment problem. *NBER Macroeconomics Annual, 1*, 15-78.

[21] Burt, R. S. (2004). Structural holes and good ideas. *American Journal of Sociology, 110*(2), 349-399.

[22] Davis, S. J., & Haltiwanger, J. (1992). Gross job creation, gross job destruction, and employment reallocation. *The Quarterly Journal of Economics, 107*(3), 819-863.

[23] Diamond, P. (2011). Unemployment, vacancies, wages. *American Economic Review, 101*(4), 1045-1072.

[24] Gabaix, X. (2011). The granular origins of aggregate fluctuations. *Econometrica, 79*(3), 733-772.

[25] Glaeser, E. L., Kallal, H. D., Scheinkman, J. A., & Shleifer, A. (1992). Growth in cities. *Journal of Political Economy, 100*(6), 1126-1152.

[26] Granovetter, M. (2018). *Getting a Job: A Study of Contacts and Careers.* University of Chicago press.

[27] Holling, C. S. (1973, November). *Resilience and Stability of Ecological Systems.*

[28] Jacobson, L. S., LaLonde, R. J., & Sullivan, D. G. (1993). Earnings losses of displaced workers. *The American Economic Review*, 685-709.

[29] Lilien, D. M. (1982). Sectoral shifts and cyclical unemployment. *Journal of Political Economy, 90*(4), 777-793.

[30] Martin, R. (2012). Regional economic resilience, hysteresis and recessionary shocks. *Journal of Economic Geography, 12*(1), 1-32.

[31] Moretti, E. (2010). Local multipliers. *American Economic Review, 100*(2), 373-377.

[32] Neffke, F., Henning, M., & Boschma, R. (2011). How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. *Economic Geography, 87*(3), 237-265.

[33] Newman, M. E. J. (2010). *Networks: An Introduction.* Oxford, UK: Oxford University Press.

[34] Pareliussen, J. K., & Hwang, H. (2018). Benefit reform for employment and equal opportunity in Finland. *OECD Economic Department Working Papers,* (1467), 1-39.

[35] Pastor-Satorras, R., Castellano, C., Van Mieghem, P., & Vespignani, A. (2015). Epidemic processes in complex networks. *Reviews of Modern Physics, 87*(3), 925-979.

[36] Simmie, J., & Martin, R. (2010). The economic resilience of regions: towards an evolutionary approach. *Cambridge Journal of Regions, Economy and Society, 3*(1), 27-43.

How to cite this article: Zhen Xiong (2024). Dynamic Labor Flow Networks and Shock Propagation, Firm Dynamics, and Regional Resilience. *Bulletin of Computer and Data Sciences*, 5(3), 1-20. DOI: 10.71448/bcds2453-1

Received: 24/02/2024 **Revised:** 14/06/2024 **Accepted:** 21/06/2024 **Publish:** 30/09/2024

AND DATA SCIENCES BULLETIN OF COMPUTER *Bulletin of Computer and Data Sciences* is a peer-reviewed open access journal.