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ECONOMIC INTERDEPENDENCIES IN THE GREAT LAKES–ST. LAWRENCE REGION: A DYNAMIC ANALYSIS OF MANUFACTURING CONNECTEDNESS

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Economic Interdependencies in the Great Lakes–St. Lawrence Region: A Dynamic Analysis of Manufacturing Connectedness[*]

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Abstract/Résumé

This study investigates the evolving dynamics of economic connectedness within the Great Lakes–St. Lawrence (GLSL) region, focusing on the manufacturing sector across eight U.S. states and two Canadian provinces. Leveraging monthly manufacturing employment growth rates from January 1990 to December 2024, the analysis employs a Vector Autoregressive (VAR) model combined with Elastic Net regularization to capture the interdependencies and directional spillovers among these highly integrated regional economies. Through forecast error variance decomposition, the approach identifies the contributions of shocks originating in any given state or province to fluctuations in the others, thereby quantifying both the magnitude of influence ("Connectedness To") and the degree of exposure ("Connectedness From"). The results reveal a complex yet discernible network of industrial linkages, with states such as Ohio and Indiana emerging as consistent net transmitters of shocks and provinces like Quebec displaying relatively lower susceptibility to external disturbances. A rolling window estimation confirms that these patterns vary over time, frequently intensifying during episodes of macroeconomic stress, such as the 2008–2009 financial crisis and the onset of the COVID-19 pandemic. The findings highlight the significance of coordinated policy interventions aimed at stabilizing key nodes in the network and underscore the importance of diversification and risk management strategies for entities that exhibit heightened exposure.

Cette étude examine l'évolution de la dynamique des liens économiques dans la région des Grands Lacs et du Saint-Laurent (GLSL), en se concentrant sur le secteur manufacturier dans huit États américains et deux provinces canadiennes. S'appuyant sur les taux de croissance mensuels de l'emploi dans le secteur manufacturier de janvier 1990 à décembre 2024, l'analyse utilise un modèle vectoriel autorégressif (VAR) combiné à une régularisation Elastic Net afin de saisir les interdépendances et les retombées directionnelles entre ces économies régionales hautement intégrées. La décomposition de la variance des erreurs de prévision permet d'évaluer l'influence (« Connectedness To ») et l'exposition (« Connectedness From ») de chaque juridiction aux chocs régionaux. Les résultats révèlent un réseau complexe mais discernable de liens industriels, avec des États tels que l'Ohio et l'Indiana qui apparaissent comme des transmetteurs nets constants de chocs et des provinces comme le Québec qui affichent une sensibilité relativement faible aux perturbations externes. Une estimation par fenêtre glissante confirme que ces tendances varient dans le temps, s'intensifiant fréquemment lors d'épisodes de tension macroéconomique, tels que

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la crise financière de 2008-2009 et le début de la pandémie de COVID-19. Les résultats soulignent l'importance des interventions politiques coordonnées visant à stabiliser les nœuds clés du réseau et mettent en évidence l'importance des stratégies de diversification et de gestion des risques pour les entités fortement exposées

Keywords/Mots-clés: Connectedness; Economic Integration; Labor; Great Lakes Saint Lawrence / Connectivité ; Intégration économique ; Secteur manufacturier ; Marché du travail ; Grands Lacs et Saint-Laurent

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1 Introduction

The manufacturing sector occupies a central place in the economic framework of the Great Lakes and St. Lawrence Region (GLSL), which comprises eight U.S. states and two Canadian provinces. This expansive area stands out as one of the world's foremost industrial clusters, yielding close to 40% of the United States' manufacturing output and nearly two-thirds of Canada's industrial production. Such formidable economic stature stems not merely from the elevated levels of production but also from the density of trade that persists among the constituent entities, creating a tightly knit network of interdependence. In fact, over half of the bilateral trade between the United States and Canada transpires within this region, where manufacturing constitutes the predominant sector.

Because of this profound degree of cross-border integration, shocks to manufacturing, whether arising from macroeconomic disturbances or local events such as natural disasters, often reverberate widely. Boehm et al. (2019), for example, document how the 2011 tsunami in Japan significantly affected U.S. industries through interlinked value chains, underscoring that a shock to any area well embedded in global supply networks can cascade into broader production systems. Analogously, a disruption in a GLSL state or province may trigger systemic consequences for the region's entire manufacturing sphere.

Given these extensive linkages, analyzing the processes through which economic shocks diffuse and pinpointing the most influential regions in this transmission process becomes crucial for policymakers intent on mitigating systemic risk in a highly integrated environment.

A key analytical tool in evaluating such interdependencies is the concept of "economic connectedness," introduced by Diebold and Yılmaz (2009, 2012, 2014). Grounded in variance decomposition from vector autoregressions, economic connectedness highlights not only the influence that a given region may exert on others but also its vulnerability to external shocks.

This dual perspective is particularly instructive because it captures bilateral linkages among state or provincial economies, while simultaneously identifying broader patterns of systemic spillovers and risk. Furthermore, economic connectedness offers a means of gauging how shocks in one entity feed into the overall volatility of the network, and how the volatility of a given entity is, in turn, affected by shocks from the rest of the network, thereby providing a comprehensive metric of both aggregate influence and aggregate exposure to disturbances.

This study examines how connectedness within the GLSL has evolved over time in the manufacturing sector and aims to address a set of interrelated research questions. First, it investigates the relative influence of each state and province within the regional network, seeking to identify whether certain areas consistently emerge as dominant "transmitters" of economic shocks. Second, it explores which states and provinces exhibit heightened exposure to shocks emanating elsewhere in the GLSL, thereby highlighting potential vulnerabilities in the event of sectoral or macroeconomic disruptions. Third, it traces the evolution of these connectedness patterns over an extended sample period, with the aim of revealing whether the role of each entity has changed in response to broader economic trends or crises. These questions are not only relevant from a theoretical standpoint, where the objective is to improve our understanding of regional interdependencies, but they also carry tangible policy implications. More granular insight into how shocks propagate can help decision-makers target strategic investments or sector-specific interventions that bolster resilience in critical nodes of the supply chain. By setting its analytical focus at the level of individual states and provinces, this study advances the current literature on connectedness in two principal ways. It contributes fresh evidence on cross-border manufacturing interconnectedness within a major production hub in North America, complementing studies that have so far concentrated primarily on national-level aggregates (Greenwood-Nimmo et al., 2021; Pham, and Sala, 2022; Takongmo and Toure, 2023) or purely financial spillovers (Baruník, et al, 2016; Diebold and Yılmaz 2015; Demirer et .al, 2018; Umar et .al, 2022). In addition, it capitalizes on a methodologically robust approach, rooted in the vector autoregression framework with Elastic Net regularization, to handle potentially high-dimensional data, thereby enhancing both the precision of the estimates and the reliability of the subsequent policy recommendations.

The following investigation intends to uncover the principal nodes of influence and exposure in the manufacturing sector across the GLSL region and to establish how these interdependencies unfold across time. By elucidating the strength, direction, and fluctuations of cross-border economic spillovers, the study aspires to inform strategies that could fortify the region's capacity to withstand future shocks, whether those arise from localized supply disruptions or from global economic dislocations.

2 Literature Review

The scholarly literature on regional economic interdependence and connectedness has expanded considerably in recent decades, reflecting a heightened interest in how local shocks propagate across broader networks of trade and production. Early contributions on regional integration between Canada and the United States, such as McCallum (1995), documented that national borders continue to exert a strong influence on trade flows despite shared language and cultural affinities. Since then, more nuanced approaches have appeared, attributing cross-border synergies to the depth of interlinked supply chains, cross-investment patterns, and labor market dependencies.

Against this backdrop, the Great Lakes and St. Lawrence (GLSL) region has received particular attention, given its role as one of the densest manufacturing and trade corridors in North America. Studies by Wonnacott (2011) and Anderson and van Wincoop (2003) have long suggested that proximity and institutional alignment, especially after the North American Free Trade Agreement (NAFTA), could result in a heightened level of regional integration, in which internal frontiers matter less than sectoral specificities.

As the empirical literature began focusing on how regional shocks travel within and across borders, methodological approaches evolved to capture the direction and intensity of spillovers. Diebold and Yılmaz (2009, 2012, 2014) pioneered a suite of connectedness metrics that build upon the vector autoregressive (VAR) framework to trace how variance in one entity's variable can be explained by innovations in others. Their approach has proven particularly suitable for exploring intricate networks, such as financial systems or heavily integrated manufacturing belts.

A key insight from this strain of research is that system-wide volatility can be decomposed to reveal not only who influences whom, but also to what extent each entity stands exposed to foreign shocks. This perspective aligns with broader concerns in macroeconomics about systemic risk, previously discussed in Billio et al. (2012), who highlighted that connectedness metrics can be instrumental in detecting potential fault lines in an interdependent economic system. Although Billio and colleagues concentrated on financial institutions, the conceptual apparatus remains valid for examining real-sector networks in which production bottlenecks or labor market disruptions might spread swiftly from one region to another.

In the specific context of manufacturing, several studies examine how localized shocks, such as natural disasters, can reverberate through globally distributed production chains. Boehm et al. (2019) illustrate how the 2011 Tōhoku earthquake in Japan rippled outward, affecting U.S. manufacturers that relied on imported inputs. Their findings emphasize the importance of production connectivity: when industries are deeply interwoven, a supply disruption in one node can trigger cascading effects throughout the entire network.

Though Boehm et al. concentrate on an international phenomenon, parallels can be drawn to the GLSL region, where many states and provinces engage in dense cross-border manufacturing ties, especially in the automotive, machinery, and chemical industries. Recent scholarship on supply chain resilience, including Jiang et al. (2020), extends these concerns to strategic policy interventions aimed at reducing vulnerability to sudden shocks.

Within the Great Lakes economic geography, the question of shock transmission has roots in older streams of research on U.S.-Canada business cycle synchronization, an area once characterized by conflicting findings about the degree to which these two economies move in tandem. Backus, Kehoe, and Kydland (1992) posited that advanced industrial nations, such as the United States and Canada, experience parallel cyclical movements due to shared demand sources, common technology shocks, and tight commercial linkages. This insight contributed to subsequent inquiries into cross-regional transmissions, indicating that geographic and institutional proximity may magnify the intensity of spillovers.

More granular analyses zeroed in on subnational regions, confirming that manufacturing-heavy locales in the United States and Canada often move together, a pattern partly attributed to the automotive corridor extending across Michigan, Ontario, and Ohio. Yet, until relatively recently, empirical treatments of these interdependencies lacked sophisticated modeling tools that could parse out the relative influence or exposure of each subnational entity.

The introduction of the Diebold-Yılmaz connectedness framework addressed many of these limitations by offering a way to disentangle bilateral and system-wide linkages. In the realm of manufacturing, this method has been applied to study how shocks diffuse not only through direct trading relationships but also through input-output linkages in production. Studies like Chen and Juvenal (2016) adopt similar structural VAR setups, albeit sometimes with different estimation techniques, to unveil the intricate paths whereby local labor market conditions mirror broader shifts in cross-border supply and demand.

More advanced regularization methods, including LASSO and Elastic Net, have recently been incorporated to cope with the high dimensionality often present when multiple states or provinces are included in a single model. This approach is particularly crucial for the GLSL region, which encompasses numerous jurisdictions, each with distinct industrial profiles, labor-market policies, and trade exposures.

A parallel body of work focuses on the policy implications of connectedness. Scholars often argue that identifying the "most central" or "most influential" regions in a network is critical for designing interventions that reduce systemic vulnerability. For instance, in a network where Ohio exerts a disproportionately large influence on other GLSL states through automotive supply chains, a recession in Ohio's labor market could propagate quickly, lifting unemployment across neighboring jurisdictions.

Policymakers might respond by targeting coordinated monetary or fiscal policies that shore up demand in these pivotal states, or they might encourage supply-chain diversification to cushion negative spillovers. From the perspective of net receivers, states or provinces characterized by high exposure to external shocks may implement labor-market reorientation or invest in alternative industries to mitigate dependency on adjacent regions' fortunes. Such strategies build on the foundational assumption, articulated in the connectedness literature, that the structure of interdependence must be clearly mapped before prudent decisions can be undertaken.

Overall, the literature has evolved from broad theories of trade integration and country-level business cycle synchronization to more refined models that trace how shocks propagate within complex networks. The application of Diebold-Yılmaz connectedness techniques in this field marks a significant methodological leap, enabling the detection and quantification of transmission channels among states and provinces in the Great Lakes and St. Lawrence Region. By linking these advanced econometric methods with practical policy considerations regarding systemic risk and supply-chain resilience, current research underscores that understanding interconnectedness is a necessary condition for effective economic governance in an era of ever-tightening regional integration.

3 Methodology and Data

Diebold and Yilmaz (2009, 2012 and 2014) introduced a method for quantifying connectedness among economic entities through the decomposition of forecast error variances of each entity's time series. To apply this methodology to the Great Lakes–St. Lawrence (GLSL) region,the third economy in the worl, the present analysis follows three main steps.

First, a Vector Autoregressive (VAR) model is selected to represent interactions among the U.S. states and Canadian provinces in this region. Second, the VAR parameters are estimated using the Elastic Net method. Third, connectedness measures are computed based on the generalized forecast error variance decomposition. This section outlines these steps and introduces the data employed in the study.

3.1 VAR Model

A central objective of this study is to understand how shocks in manufacturing employment disperse across the Great Lakes and St. Lawrence (GLSL) region, identifying which states and provinces emerge as dominant transmitters or receivers of these shocks and how these roles evolve over time.

To meet this objective, the Vector Autoregressive (VAR) model offers a comprehensive statistical framework for examining interdependencies among multiple time series variables without imposing a priori restrictions on exogeneity or causal ordering.

Let Y_t be a k-dimensional vector representing economic indicators of GLSL states and provinces at time t. A VAR(p) model is expressed as:

$$Y_t = \sum_{i=1}^{p} A_i Y_{t-i} + e_t \tag{1}$$

where A_i are coefficient matrices of size $k \times k$, and e_t is a white noise vector with mean zero and covariance matrix Σ.

The number of lags, p, is set to six months, allowing us to capture medium-term economic dependencies.

By allowing each variable to depend on its own past realizations as well as the past values of all other variables in the system, the VAR framework accommodates a rich web of dynamic feedback effects. This flexibility aligns with the study's research aim of tracing how disturbances originating in a single state or province might propagate within a tightly integrated manufacturing network.

Rewriting the VAR in its moving average (MA) form brings the model closer to the connectedness measures. Specifically, one obtains:

$$Y_t = B(L)e_t, \text{ where } B(L) = (I - A(L)L)^{-1} \tag{2}$$

Here, $A(L)$ is the polynomial in the lag operator L, and $B(L)$ represents the infinite MA expansion of the system. This representation is instrumental for the subsequent forecast error variance decomposition, which isolates the contribution of shocks from any individual state or province to the forecast errors of other entities in the system.

In the context of the research question, this decomposition is crucial for quantifying each entity's influence, or "transmission power", relative to its exposure, or "reception", when unexpected changes arise in other parts of the GLSL manufacturing network.

The VAR specification is particularly well suited for examining time-varying linkages when coupled with a rolling window estimation scheme. By estimating the VAR parameters over a 60-month rolling window, one can observe how the contributions of each state or province to the system's forecast error variance shift across different phases of the business cycle, financial disruptions, or localized economic events. This methodological choice thus provides a dynamic perspective on connectedness, illuminating whether the roles of key transmitters or receivers remain stable or change fundamentally in response to major economic shocks.

3.2 Elastic Net Estimation

While the VAR model furnishes a theoretically appealing approach, practical difficulties can arise when the dimensionality of the system is high or when certain states and provinces exhibit collinear or near-collinear employment patterns. Estimating large-scale VARs by ordinary least squares can lead to overfitting and instability, especially if the number of lagged parameters grows large relative to the sample size.

To address these issues, this study adopts the Elastic Net estimator, which provides a balance between parsimony and flexibility by integrating penalties from the Lasso and Ridge regression methods (Zou and Hastie, 2005). For a single equation in the VAR(p) model, one may reformulate the problem as a linear regression:

$$y_{it} = X_t A + u_t \tag{3}$$

where $A = [A_{1,1}, A_{1,2}, ..., A_{k,p}]'$ is the coefficient vector and $X_t = [y_{1,t-1}, ..., y_{k,t-p}]'$ is the matrix of lagged values. The Elastic Net estimator for A is given by:

$$A_{EN} = \text{argmin}_A \, \|y - XA\|_2^2 + \lambda \left(\alpha \sum_{j=1}^{p} \sum_{i=1}^{k} A_{i,j}^2 + (1-\alpha) \sum_{j=1}^{p} \sum_{i=1}^{k} |A_{i,j}| \right) \tag{4}$$

where λ controls the overall regularization strength, and α determines the balance between Lasso ($\alpha = 0$) and Ridge ($\alpha = 1$). For our analysis, we determine α and λ through cross-validation.

From the perspective of the research question, the Elastic Net estimator proves valuable in situations where different entities' employment time series are highly correlated. Such collinearities can obscure the precise origins of inter-state or inter-provincial shocks and lead to inflated parameter estimates if standard, non-regularized approaches were used. Elastic Net's hybrid penalty, on the other hand, shrinks insignificant parameters toward zero while moderating the magnitude of those with moderate explanatory power. This approach yields a VAR representation that remains faithful to the underlying data, thereby strengthening the reliability of subsequent forecasts and variance decompositions used to measure economic connectedness.

3.3 Connectedness Measures

Having estimated the VAR(p) model, the study employs forecast error variance decomposition to quantify how each state or province's manufacturing employment shocks contribute to variations in the remaining entities. The central innovation behind the Diebold-Yılmaz (2012) connectedness framework lies in decomposing the forecast error variance at a specified horizon H. Given the moving average representation the share of forecast error variance at horizon H of state/province i

due to a shock in j is computed as:

$$D_{ij}^{H} = \frac{\sigma_{jj}^{-1} \sum_{l=0}^{H-1} (\iota_i' B_l \iota_j)^2}{\sum_{l=0}^{H-1} (\iota_i' B_l \Sigma B_l' \iota_i)} \tag{5}$$

where σ_{jj} is the variance of shocks to j, and ι_i is a unit vector selecting the relevant element (Pesaran and Shin, 1999).

Normalizing by row sums ensures that contributions sum to unity:

$$d_{ij}^{H} = \frac{D_{ij}^{H}}{\sum_{i=1}^{k} D_{ij}^{H}} \tag{6}$$

The following measures summarize regional economic connectedness:

- **Directional Connectedness To ($C_{\bullet\leftarrow i}^{H}$)**: Measures the impact of state/province i on others.
- **Directional Connectedness From ($C_{i\leftarrow\bullet}^{H}$)**: Quantifies how much a state/province is influenced by external shocks.
- **Total Connectedness (C^{H})**: Reflects the overall level of interconnectedness in the region.

To investigate changes over the multi-decade sample, the study implements a rolling window of 60 months for VAR estimation, coupled with a 6-month forecast horizon. This technique illuminates potential shifts in each entity's capacity to transmit shocks, as well as shifts in its susceptibility to external conditions. These insights directly answer the main research question by revealing which states and provinces consistently act as drivers of regional fluctuations, which tend to be net recipients of shocks, and whether such roles remain stable or are sensitive to evolving macroeconomic contexts. In a region where policy coordination and rapid response to industrial slowdowns can have profound economic implications, understanding the nature and trajectory of connectedness is essential. By systematically tracing these interdependencies through variance decomposition, the study provides a structured empirical basis for both economic theory and practical policy design.

3.4 Data

Manufacturing employment growth rates[1] for the GLSL states and provinces form the linchpin of the empirical investigation, serving as the principal variable in the Vector Autoregressive (VAR) framework. These series, which are observed monthly over the extended period spanning January 1990 through December 2024, allow for the examination of both medium- and long-run variations in the regional manufacturing labor market. Because manufacturing constitutes a significant component of the overall economic output in each state or province, trends in sectoral employment

[1] Table 3 presents the descriptive statistics for the manufacturing employment growth rates across states and provinces in the Great Lakes-Saint Lawrence (GLSL) region. The growth rate is calculated as the first difference of the natural logarithm of employment levels, $\Delta \log(E_t) = \log(E_t) - \log(E_{t-1})$.

often mirror more general changes in production and trade patterns, thereby offering an informative proxy for real activity within and across borders.

The choice of this extended time horizon reflects a desire to incorporate several phases of the business cycle, including recessions (for instance, those occurring in the early 1990s, early 2000s, and during the financial crisis of 2008–2009), as well as periods of recovery or expansion. By covering multiple economic cycles, the dataset captures not only expansions, when manufacturing capacity tends to scale up in tandem with surging demand, but also contractions, when shocks to national or international markets transmit swiftly to labor indicators. This broader scope enriches the VAR estimation, which benefits from the presence of cyclical and structural shifts in manufacturing employment.

A key advantage of relying on monthly observations, rather than quarterly or annual data, is the increased granularity in capturing shorter-term fluctuations in the manufacturing workforce. Such higher-frequency data illuminate sudden adjustments—whether expansions, contractions, or pivots prompted by macroeconomic events—while still permitting the analysis of underlying trends when aggregated over longer horizons. The manufacturing sector in this region is known for its pronounced sensitivity to changes in domestic and foreign demand. Exchange rate movements, shifts in global supply chain configurations, and trade policy adjustments can all manifest in swift reconfigurations of employment structures, the timing of which is more precisely tracked with monthly data.

Figure 1 depicts the evolution of manufacturing employment across the ten states and provinces included in the analysis. Although these entities exhibit broadly synchronized cycles—attesting to the high degree of integration in the GLSL region—disparities emerge in both the magnitude of employment gains and the timing of slowdowns. In some states, such as those with extensive automotive or machinery production, employment growth tends to closely shadow U.S. and global economic swings, revealing acute spikes or dips tied to international demand. Meanwhile, certain provinces, owing to variations in labor regulations, currency effects, or diversification into alternative sectors, register distinct patterns that may differ from their cross-border counterparts, at least in the short to medium run.

Notably, Figure 1 reveals that while most GLSL constituents experience analogous overarching trends—such as a pronounced downturn during the global financial crisis and a sudden contraction in early 2020—there remain nuanced oscillations that can be more pronounced in specific jurisdictions. This variation underscores the potential for asymmetric spillovers within the network of states and provinces. Even among entities that share highly integrated supply chains, local factors—such as tax policies, wage-setting mechanisms, or sector-specific developments—can accentuate or mitigate external shocks, thereby producing divergent trajectories in manufacturing employment. Such heterogeneity is significant for the connectedness analysis: it is precisely in these discrepancies that one may find the origins of asymmetric shock transmission, where one state's shortfall in production reverberates more strongly in certain trading partners than in others.

Taken together, these data constitute a robust empirical foundation for studying the transmission of shocks within a dynamic region known for its dense economic linkages. By focusing on

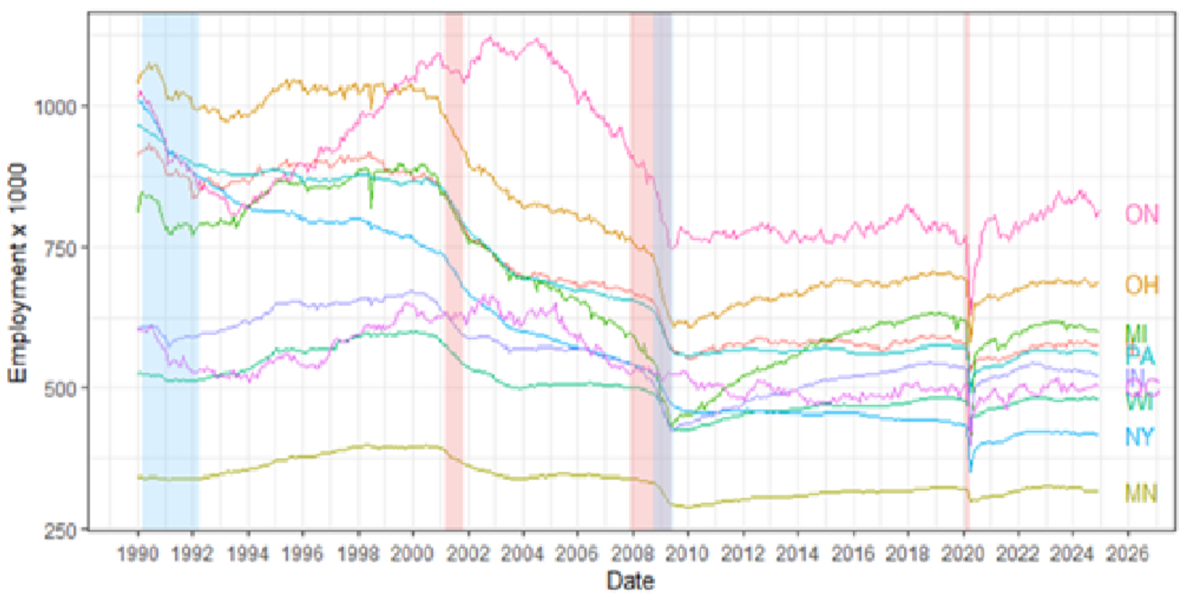

Figure 1: Manufacturing employment in the Great Lake states/provinces

Note: This graphic presents the evolution of the manufacturing employment in the states and provinces of the GLSL region.

manufacturing employment, the analysis aligns with the reality that this sector consistently acts as a bellwether for broader economic health in the GLSL region. Through monthly granularity and a multi-decade scope, the study is positioned to capture the interplay between internal (i.e., local or domestic) and external (i.e., cross-border or global) forces that shape the course of employment trajectories. As the empirical core of the VAR model, these data thus allow a nuanced view of how interconnected labor markets respond to, and in turn transmit, economic disturbances in an environment characterized by intense trade and industrial specialization.

4 Results

This section analyzes the connectedness of the Great Lakes and St. Lawrence Region (GLSL) states and provinces. The analysis is twofold: First, we examine static connectedness using the full sample data. Second, we explore the dynamic connectedness using rolling window estimations.

4.1 Static Connectedness

Our static analysis utilizes monthly growth rates of manufacturing employment for all ten GLSL states/provinces, spanning from January 1990 to December 2024. To determine static connectedness, we first estimate a Vector Autoregression (VAR) model using Elastic Net regularization. Subsequently, we calculate variance decompositions and corresponding connectedness measures at a 6-month horizon (H = 6) using the estimated VAR parameters. Table 1 presents the results of the variance decomposition, the connectedness table.

Table 1: Full Sample GLSL Economic Connectedness.

	IL	OH	MN	MI	WI	PA	NY	IN	QC	ON	FROM
IL	44.14	23.79	3.24	4.71	6.43	5.15	3.43	5.06	1.78	2.28	55.86
OH	21.74	38.88	2.58	8.45	5.76	4.89	4.95	7.35	2.07	3.33	61.12
MN	3.94	3.88	48.13	4.38	10.35	9.51	7.12	7.49	2.37	2.82	51.87
MI	4.90	9.24	3.57	45.29	5.81	5.75	6.75	11.49	3.02	4.18	54.71
WI	5.94	6.30	8.00	5.63	43.64	10.25	7.09	7.44	1.93	3.77	56.36
PA	4.71	5.25	7.50	5.44	10.64	45.70	8.53	7.63	1.80	2.80	54.30
NY	3.03	5.75	5.51	6.92	7.39	8.81	48.61	8.53	2.32	3.13	51.39
IN	4.39	7.68	5.60	10.86	6.91	7.38	7.52	43.42	2.07	4.17	56.58
QC	2.41	2.97	2.75	3.80	2.69	2.60	3.01	2.56	74.38	2.82	25.62
ON	2.87	4.94	3.11	5.42	5.25	4.09	3.79	5.67	2.81	62.06	37.94
TO	53.93	69.80	41.86	55.62	61.23	58.42	52.19	63.24	20.17	29.31	Index
NET	-1.94	8.67	-10.00	0.91	4.87	4.12	0.80	6.66	-5.45	-8.63	50.58

Note: Each cell in the upper left 10x10 matrix gives the relative contribution of each columnar entity to the variance of the row entity's forecast error. The "FROM" column reports the share of the forecast error variance for the entity in the row, attributable to others. It represents the exposure of the entity to the GLSL. The "TO" line reports the total contributions of the entity in the column to the forecast error variance of all other entities and represents the influence of the entity on the GLSL. The "NET" reports each entity's difference between its influence and its exposure. The total connectedness index in the lower right cell is the average of the items in the "TO" row (which is also the average of the "FROM" column), multiplied by 100. Let us take Illinois (IL) as an example. Its exposure is 55.86 %, its influence is 53.93 %, and the net influence is -1.94 %. The contribution of the Ohio (OH) to the forecast error variance of Illinois's manufacturing employment is 23.79 %, while the contribution of Illinois to that of the forecast error variance of the Ohio is 21.74 %.

Each cell in the upper left 10x10 matrix gives the relative contribution of each columnar entity to the variance of the row entity's forecast error. The "FROM" column reports the share of the forecast error variance for the entity in the row, attributable to others. It represents the exposure of the entity to the GLSL. The "TO" line reports the total contributions of the entity in the column to the forecast error variance of all other entities and represents the influence of the entity on the GLSL. The "NET" reports each entity's difference between its influence and its exposure. In this network, the most influential entity or the entity with highest connectedness to others ($C^H_{\bullet\leftarrow i}$) is Ohio with 69.80 points of total influence. This reflects that on average shocks in Ohio manufacturing employment have the largest total contribution in the network entities' manufacturing employment forecast error variance. The most affected entities by the Ohio shock are Illinois, Michigan, and Indiana. The second and third most influential entities are Indiana and Wisconsin with respectively 63.24 points and 61.23 points of the total impact. Quebec is the less influential with 20.17 points of impact. The most exposed entity or the entity with highest connectedness from others (measured by ($C^H_{i\leftarrow\bullet}$)) is Ohio, of which 61.12% of its forecast error variance is associated with foreign shocks. An important part of this exposure comes from the Illinois (21.74 points) Michigan (8.45 points) and Indiana (7.35 points). Quebec is the least exposed entity with 25.62 % of its forecast error variance associated with foreign manufacturing employment shocks. This low connectedness from others in the Quebec could be explained by the relatively more rigid job market compared to the other GLSL entities.

Turning to other U.S. states, Indiana (IN) also ranks high in total influence (63.24). Beyond large-scale production activities, Indiana's advanced manufacturing sector has sustained tight cross-border relationships, allowing local shocks—whether positive or negative—to propagate readily. By contrast, states such as Minnesota (MN) exhibit lower "TO" scores (41.86) but still maintain a moderate degree of cross-border interactions owing to a diverse industrial structure that includes medical devices and food processing. The net measures for these states reveal interesting contrasts: whereas Indiana (+6.66) and Wisconsin (+4.87) appear predominantly as net transmitters, Minnesota's net value of -10.00 indicates that, on balance, it is a net recipient of shocks. This contrast suggests that Minnesota's manufacturing base is less oriented toward creating systemic shocks, yet it remains susceptible to the broad regional environment.

In the Canadian context, Quebec (QC) displays the highest level of self-driven variance in its manufacturing employment, as reflected by the fact that 74.38% of its forecast error variance cannot be attributed to other GLSL regions. This relative insulation may stem from the province's industrial composition, labor regulations, or unique linguistic and cultural framework, all of which could diminish the extent of cross-border spillovers. Nonetheless, Quebec remains somewhat connected, with a "TO" score of 20.17 indicating that it does exert a nontrivial influence on its counterparts, albeit substantially lower than states like Indiana or Ohio. Ontario (ON), meanwhile, stands between these two extremes. Ontario's manufacturing linkages, especially in the automotive corridor with Michigan and Ohio, make it a more integral participant in cross-border dynamics than Quebec, as evidenced by a higher "TO" value (29.31). However, Ontario still has a net influence of -8.63, showing that it functions more as a net receiver than a transmitter.

These observations, taken together, speak directly to the broader research questions about how regional integration in manufacturing is distributed across GLSL entities. The table points to a few critical hubs (e.g., Ohio, Indiana, Illinois, and Wisconsin) that seem to drive much of the system-wide connectivity. For policymakers, recognizing where and how shocks tend to originate or spread can be pivotal. States or provinces with high exposure might consider broadening their industrial base or engaging in cross-border coordination to mitigate vulnerability. At the same time, those with outsized influence might prioritize stabilizing their local labor markets to forestall cascading disruptions in neighboring jurisdictions. Finally, the total connectedness index (50.58) reveals that just over half of the variability in manufacturing employment is explained by cross-entity linkages. This moderate—but still substantial—figure underscores that while local factors remain important, regional spillovers play a crucial role in shaping economic outcomes. Understanding this interplay is essential for both theoretical perspectives on economic integration and practical initiatives—ranging from joint workforce development programs to coordinated responses in times of crisis—that aim to bolster regional manufacturing resilience. The remaining 48.42 % is associated with domestic conditions in the manufacturing's job market.

4.2 Dynamic Connectedness

The next stage of the analysis explores how connectedness in the GLSL region evolves over time. The same VAR methodology is applied using a 60-month rolling window, thus generating a set of time-varying connectedness indicators. The discussion highlights trends in both the overall, system-wide connectedness index and the total directional connectedness measures.

4.2.1 Dynamic System-wide Connectedness

Figure 2 illustrates the rolling window estimates of system-wide connectedness. The estimates show that interdependence among the ten GLSL states and provinces frequently intensifies during times of economic duress, including the early 2000s recession in the United States, the global financial crisis of 2009, and the pandemic-related downturn beginning in 2020. These episodes underscore the way shocks in one or more entities propagate throughout the regional network, thereby amplifying the overall level of interconnectedness.

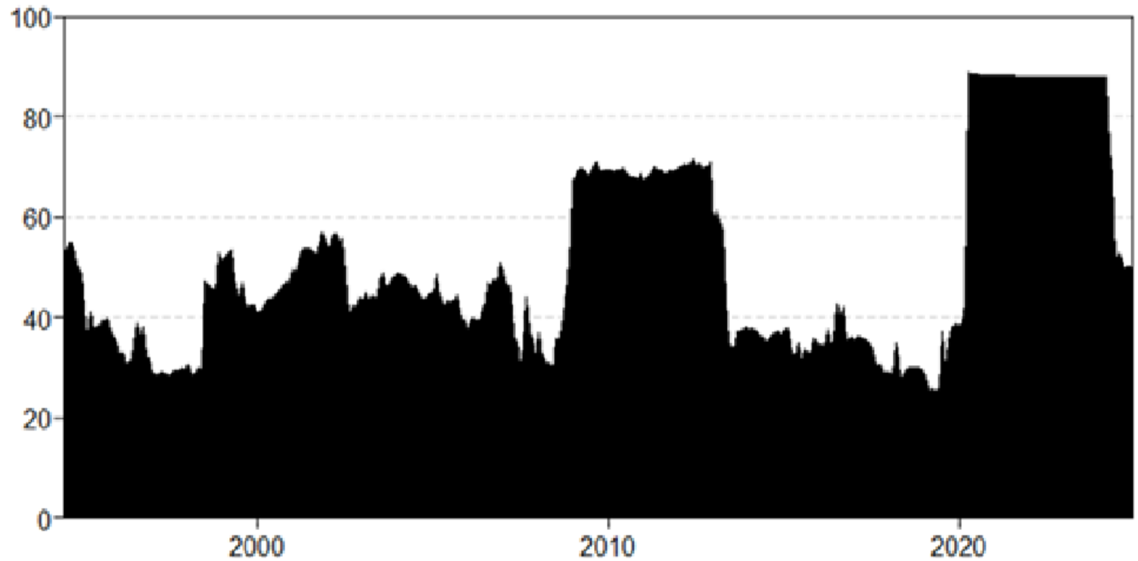

Figure 2: Rolling Sample System-Wide GLSL Economic Connectednesss.

Note: This graphic presents the evolution of the system-wide economic connectedness of the GLSL region.

4.2.2 Dynamic Total Directional Connectedness

Figure 3 displays the rolling estimates of "Connectedness From Others," capturing for each state or province the proportion of its forecast error variance that is attributable to external shocks. By illustrating how a given entity's vulnerability to shocks from elsewhere in the Great Lakes and St. Lawrence (GLSL) region fluctuates over time, this measure highlights the dynamic nature of cross-border linkages in manufacturing employment. In light of our research questions, the patterns in Figure 3 yield several important insights. First, and most generally, the rolling estimates underscore that no single entity remains immune to external disturbances; however, they also show that the degree of external influence varies considerably across states and provinces. Some entities exhibit persistently higher "Connectedness From Others," suggesting that their manufacturing employment structure—and its underlying supply chains—depend more heavily on developments unfolding in neighboring economies. In contrast, other states and provinces show comparatively lower levels of external exposure, indicating that local factors dominate fluctuations in their employment growth.

These cross-entity differences in “Connectedness From Others” respond to at least two of the study’s core questions. They shed light on which entities act as net receivers of shocks, and they illuminate how that reception level shifts in response to major macroeconomic disruptions. For example, periods of heightened global or regional turbulence, such as the 2009 financial crisis or the 2020 downturn triggered by the COVID-19 pandemic, might coincide with a general rise in “Connectedness From Others.” During these episodes, the figure typically reveals sharper spikes for all states and provinces, signifying that local manufacturing employment dynamics become more tightly synchronized with trends or shocks emanating from the rest of the GLSL region. Moreover, the rolling window approach permits a finer examination of whether certain entities that initially appear less integrated—perhaps due to more rigid labor market institutions or alternative industrial structures—eventually converge toward the more highly exposed group in times of systemic stress. By tracking these patterns, researchers and policymakers gain a clearer perspective on whether the region’s integration intensifies temporarily during crises (with a subsequent return to lower vulnerability) or whether such shocks engender a lasting shift in regional interconnectedness. With respect to policy implications, sustained or rising “Connectedness From Others” for a particular state or province signals the importance of bolstering risk management practices at local levels, including the diversification of supply chains and targeted labor market interventions. From a broader standpoint, the documented variation in exposure across the GLSL region has direct bearing on strategies aimed at enhancing resilience: if some states or provinces prove consistently susceptible to external shocks, then region-wide initiatives could be tailored to reinforce their capacity to adapt when manufacturing slowdowns or disruptions occur in neighboring jurisdictions. Figure 3’s mapping of “Connectedness From Others” provides a window into the mechanics of regional spillovers and complements the analysis of “Connectedness To Others.” Together, these measures capture both sides of the systemic risk equation—transmission and reception—and, when considered over time, they enrich the understanding of how each GLSL economy’s manufacturing sector is embedded in, and potentially impacted by, the broader cross-border network. Such granularity in detecting shifts in exposure patterns constitutes a significant step toward addressing the research questions on which entities drive the network, which remain most vulnerable, and how these roles evolve under changing economic conditions.

In this context, Figure 4 illustrates “Connectedness To Others,” representing the share of other entities’ forecast error variances attributable to shocks originating in a specific state or province. In other words, it measures the extent to which each entity serves as a driver or transmitter of shocks within the GLSL manufacturing network. By tracking these evolving patterns over a rolling window, the figure offers insight into how different states and provinces act as potential sources of systemic fluctuations, providing a valuable counterpart to the evidence reported in Figure 3 on external exposure. These trajectories of “Connectedness To Others” help identify whether some GLSL economies consistently emerge as dominant transmitters of shocks. Periods of heightened

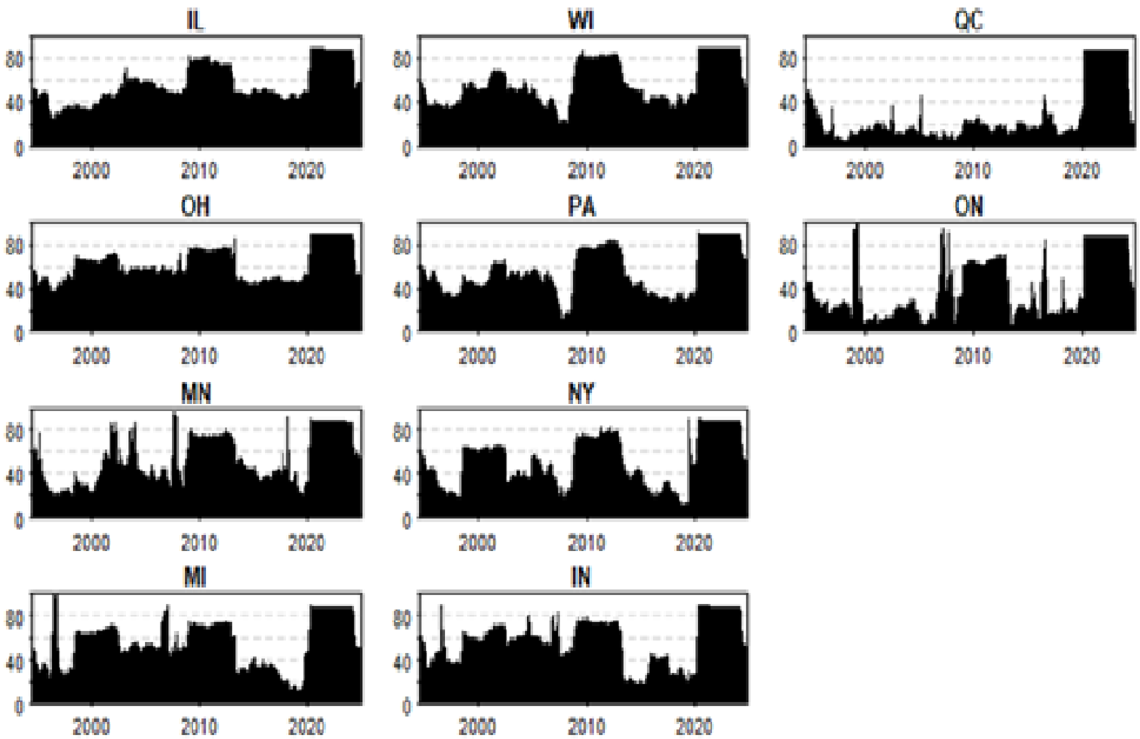

Figure 3: Rolling Sample Connectedness From Others.

Note: This graphic presents the evolution of the connectedness "From" others for each entity in the GLSL region.-.

spikes in transmission—such as during the 2009 financial crisis or the COVID-19 pandemic—often imply that one or more entities are exerting a pronounced influence on neighboring labor markets, thereby amplifying the systemic risks emanating from localized downturns. At the same time, prolonged upward trends or marked variability in transmission can signal deeper structural changes within the region. For instance, such trends may reflect the expansion of a state's or province's key industries, alterations in cross-border supply chains, or shifts in trade and investment patterns that strengthen interconnections with neighboring jurisdictions. The figure also highlights that some entities exhibit relatively stable levels of shock transmission, suggesting more diversified industrial bases or a consistent role in supplying critical inputs to other GLSL economies. By contrast, entities showing sharp cyclical fluctuations in "Connectedness To Others" may depend more strongly on volatile industries or global economic conditions, causing them to act as significant transmitters only when particular shocks arise. From a policy standpoint, knowing which states and provinces function as "shock hubs" can guide targeted interventions. If a specific entity tends to spread disturbances widely across the region, this provides a rationale for close monitoring of its industrial performance and for proactive labor-market stabilization measures, which could contain the spillover effects before they become widespread. Taken together, the insights gleaned from Figures 3 and 4 are central to addressing the study's research questions:

identifying those GLSL economies that influence many others, pinpointing which ones are most dependent on external developments, and assessing how both dynamics evolve over time. This joint perspective facilitates a more refined understanding of the underlying processes that shape not just where shocks originate, but also how they propagate, thus furnishing a stronger basis for resilience-building strategies in the region's manufacturing sector.

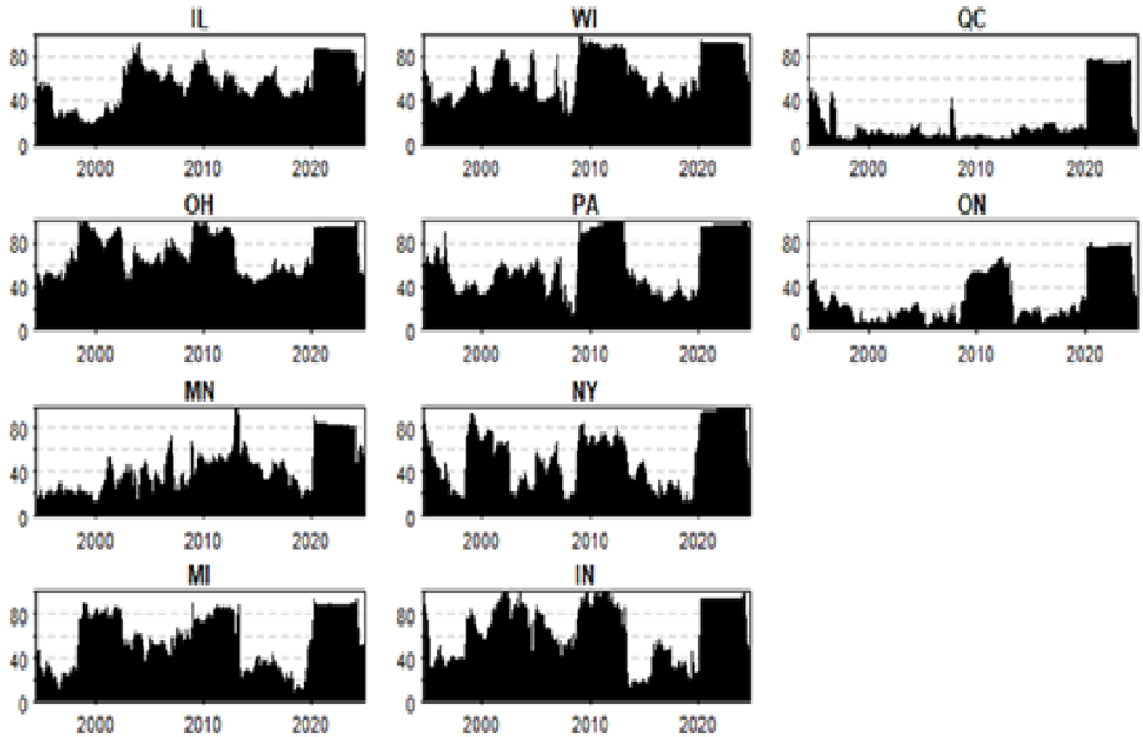

Figure 4: Rolling Sample Connectedness To Others.

Note: This graphic presents the evolution of the connectedness "To" others for each entity in the GLSL region.

Figure 5 provides a combined view of "Connectedness To Others" and "Connectedness From Others" for each state and province over the rolling sample period, thus conveying each entity's net position in the GLSL manufacturing network. Specifically, if the "net connectedness" is positive , the entity in question functions as a net transmitter of shocks, whereas negative "net connectedness" signals a net receiver. By overlaying these measures within a single illustration, the figure offers a concise depiction of how each entity's role fluctuates through time.

Viewed alongside Figures 3 and 4, these net profiles help delineate whether an entity prone to high external influence simultaneously acts as a major source of shocks for its neighbors, or conversely, whether a particularly influential state or province experiences comparatively little pressure from external disturbances. Such distinctions hold particular significance for the study's principal research questions, which center on identifying the core nodes of shock transmission, pinpointing areas of heightened vulnerability, and tracking how these dynamics evolve. Notably,

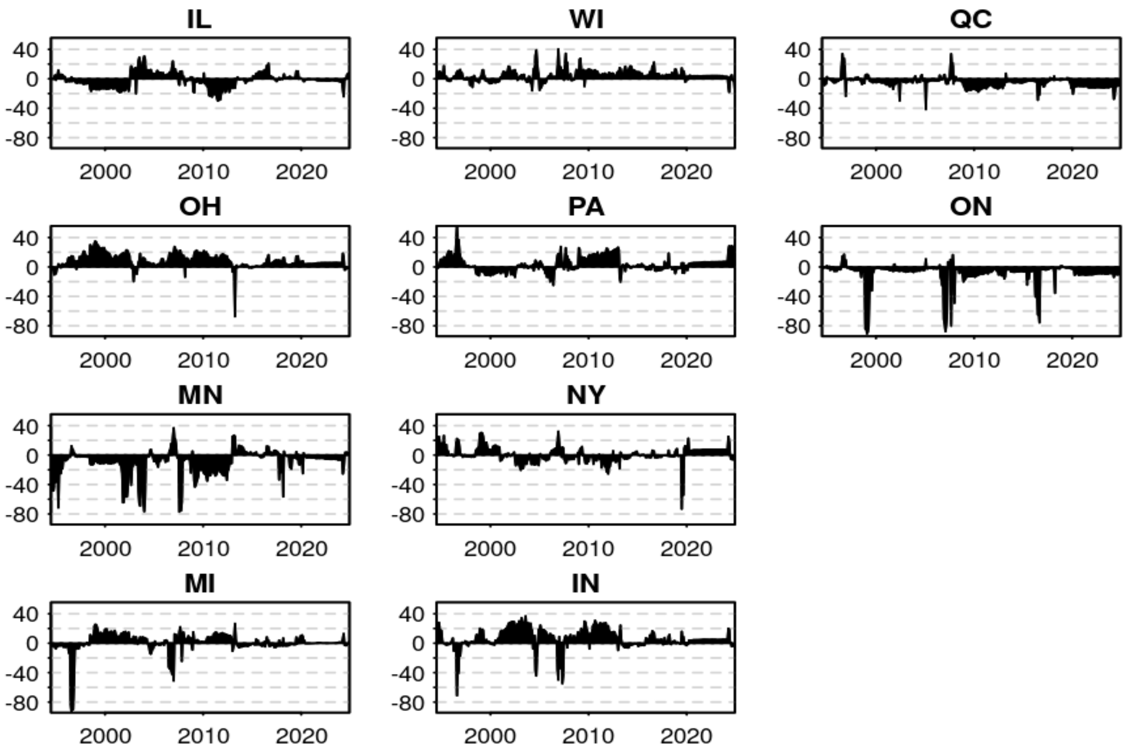

Figure 5: Rolling Sample Total Net Directional Connectedness

Note: This graphic presents the evolution of the "Net" connectedness for each entity in the GLSL region.

consistent periods in which an entity remains a net transmitter suggest that structural factors—such as robust manufacturing capacity or supply-chain centrality—persist in elevating its impact on the broader region. Meanwhile, entities switching between net transmitter and net receiver roles over various cycles may reveal a more fluid industrial base or ongoing transitions in their global and regional trading relationships. From a policy perspective, the balance between "Connectedness To" and "From" underscores where risk mitigation efforts could prove most beneficial. Entities that are persistently net receivers, for example, might merit targeted diversification strategies to moderate external shocks, whereas net transmitters may need to strengthen contingency measures that cushion domestic downturns from radiating across the GLSL region.

To summarize, Figures 3 and 4 illustrate the evolution of total directional connectedness, respectively, from others and to others, for each of the ten states and provinces. Figure 5 combines both measures in a single graphic to highlight the net position of each region in terms of shock transmission. Our findings suggest that U.S. states exhibit a broadly similar pattern in connectedness from others over time, with noticeable increases during the last three U.S. recessions (2001, 2009, and 2020). In contrast, Canadian provinces display distinct patterns. On average, they exhibit lower connectedness from others compared to U.S. states. Ontario shows a relatively higher and more volatile level of connectedness from others than Quebec.

Among U.S. states, Indiana and Ohio consistently display the highest levels of influence or connectedness to others throughout the sample period. Along with Pennsylvania and Wisconsin, they tend to act as net transmitters of shocks. In contrast, the Canadian provinces follow more distinct trajectories. On average, they exhibit weaker connectedness from others compared to U.S. states. Among the two provinces, Ontario's connectedness from others is higher and more volatile than Quebec's. With respect to transmission of shocks, Indiana and Ohio consistently stand out as the states exercising the strongest influence on the rest of the network across the sample period. Along with Pennsylvania and Wisconsin, they frequently function as net transmitters of shocks. The Canadian provinces remain the least influential, tending to absorb shocks originating in the U.S. states, although the contribution of these external shocks to their own forecast error variances remains comparatively low.

5 Conclusion

This study has examined the evolution of economic connectedness in the GLSL region's manufacturing sector through the lens of a VAR model estimated with the Elastic Net method. By focusing on manufacturing employment growth rates at a monthly frequency over several decades, the analysis has enabled a granular perspective of how shocks in one state or province reverberate throughout the broader regional network. In addressing the core research questions—namely, identifying the most influential transmitters of shocks, highlighting the most exposed recipients, and documenting how these roles have shifted over time—the results point to a complex, yet discernible hierarchy of economic interdependence. States such as Ohio and Indiana emerge as prominent transmitters, exerting substantial influence on neighboring labor markets, whereas provinces like Quebec display higher levels of self-driven variance and hence lower external exposure. Furthermore, the rolling window estimations suggest that these patterns exhibit marked time variation, with connectivity frequently intensifying during periods of macroeconomic distress.

These findings carry significant implications. The presence of a few dominant transmitters implies that localized disruptions can rapidly diffuse throughout the regional manufacturing sector, prompting policymakers to consider preemptive measures aimed at stabilizing the labor markets in these key nodes. Simultaneously, the considerable exposure registered by other entities underscores the need for collaborative strategies—such as supply-chain diversification and enhanced workforce retraining programs—that may help mitigate the most acute vulnerabilities. The total connectedness index further reveals that roughly half of the observed variance in manufacturing employment is linked to cross-border spillovers, highlighting that, while local dynamics remain critical, joint regional efforts can play a decisive role in managing systemic risks.

Notwithstanding the insights yielded by this approach, several limitations warrant acknowledgment. First, the VAR framework adopted here is inherently linear, which may not fully capture the possibility of nonlinear or regime-dependent relationships across states and provinces. This linearity can be especially restrictive during major structural shifts or unprecedented events, when relationships between economies may change more abruptly. Second, the study has focused exclusively on the manufacturing sector, and while this sector is crucial for regional integration, other industries—particularly services—also shape overall economic interdependence and might follow different patterns of spillovers. Third, the analysis, by necessity, condenses the complexity of labor market regulations, industrial composition, and policy differences into a single model. Local heterogeneities, including the extent of unionization, wage-setting frameworks, and production technologies, could further refine our understanding of how shocks propagate. Lastly, even though the rolling window estimation provides a dynamic angle, it remains subject to the trade-off between window size, parameter stability, and available observations.

Future research may extend these findings in several directions. Incorporating additional sectors, analyzing sub-sectors within manufacturing, or studying the delay of shock transmission between industries, would offer a more nuanced portrait of how shocks diffuse through diverse production chains. Including nonlinear or regime-switching techniques could better capture shifts in cross-border relationships during periods of acute turbulence, such as global financial crises or large-scale supply chain disruptions. Integrating variables such as exchange rates, trade policies, or regional business climate indicators would also clarify the underlying drivers of manufacturing interdependence. Ultimately, the goal is to provide policymakers with an even richer body of evidence on where vulnerabilities reside, how shocks traverse subnational and international boundaries, and how proactive measures might reinforce the resilience of the GLSL region's manufacturing landscape.

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Annex A

As a robustness check, we replicate the previous analysis by expanding the scope to include manufacturing employment in surrounding regions. To this end, we incorporate two additional variables into the dataset: manufacturing employment in all American states not within the GLSL region (RUS—Rest of US, see Figure 6) and manufacturing employment in Canadian provinces not within the GLSL region (RCA—Rest of Canada, see Figure 6).

The static and dynamic results remain qualitatively consistent. Ohio continues to be the most influential state, followed by Indiana and Wisconsin. Ohio also remains the most exposed entity within the network. Furthermore, the dynamic system-wide connectedness closely resembles the initial findings, exhibiting a correlation of 0.98 between the two time series.

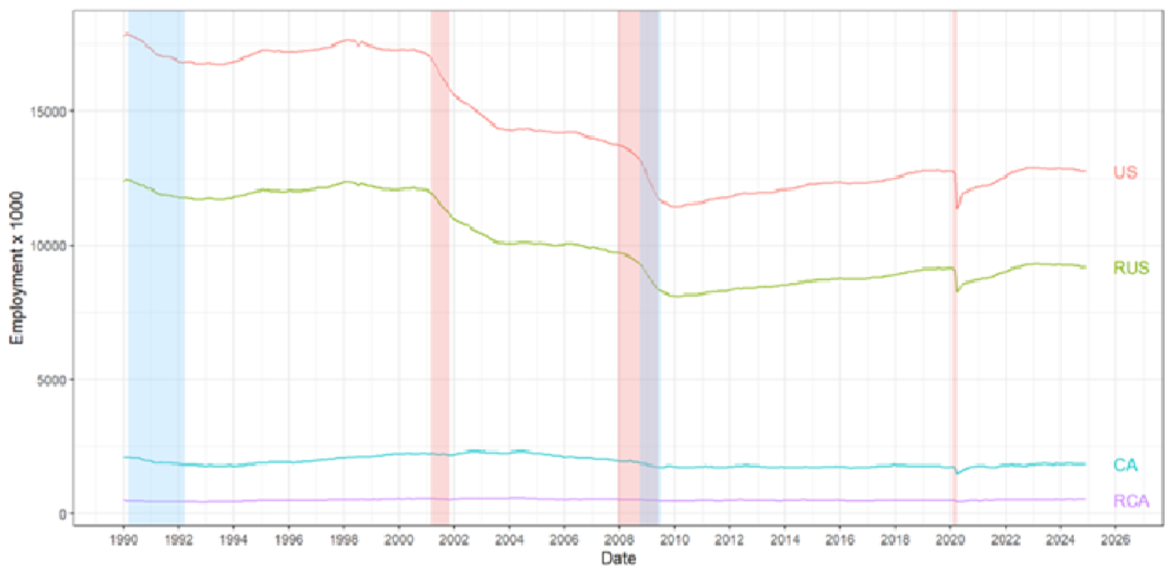

Figure 6: Manufacturing employment for other states (RUS) and other provinces (RCA).

Note: This graphic presents the evolution of the manufacturing employment in the US and Canada and the evolution of the manufacturing employment in all the rest of the states outside of the GLSL (RUS) and in all the provinces not in the GLSL region (RCA).

Table 2: Full Sample GLSL Economic Connectedness (including other states and other provinces).

	IL	OH	MN	MI	WI	PA	NY	IN	QC	ON	RUS	RCA	FROM
IL	41.94	22.6	2.75	4.59	5.93	4.49	2.92	4.66	1.63	2.05	4.7	1.75	58.06
OH	20.48	36.58	2.31	8.18	5.5	4.39	4.39	6.92	1.86	3.4	4.56	1.43	63.42
MN	3.04	3.17	47.14	4	9.34	8.39	6.13	6.52	1.93	2.33	6.58	1.42	52.86
MI	4.38	8.34	2.98	41.68	5.13	4.98	5.81	10.75	2.47	3.7	8.78	0.99	58.32
WI	5.33	5.77	7.43	5.43	40.2	8.98	6.13	6.44	1.89	3.45	7.11	1.83	59.8
PA	3.89	4.45	6.87	5.22	9.34	42.25	7.51	6.95	1.6	2.63	7.96	1.34	57.75
NY	2.42	4.83	4.77	6.54	6.33	7.57	44.68	7.69	2.16	2.85	8.69	1.47	55.32
IN	3.93	7.06	5.06	10.44	6	6.73	6.68	39.89	1.97	4.02	6.28	1.93	60.11
QC	2.22	2.79	2.79	3.6	2.53	2.3	2.86	2.33	71.34	2.71	2.96	1.57	28.66
ON	2.38	4.35	2.35	4.93	4.69	3.27	3.22	5	2.38	61.52	3.48	2.44	38.48
RUS	4.83	5.3	5.64	9.22	7.27	8.17	8.3	7.21	2.04	3	37.75	1.27	62.25
RCA	3.2	2.63	2.06	2.48	3.69	2.74	3.36	3.76	1.7	2.99	2.64	68.75	31.25
TO	56.11	71.29	45.01	64.64	65.75	62.01	57.32	68.23	21.62	33.13	63.74	17.43	Index
NET	-1.95	7.87	-7.86	6.32	5.95	4.26	2	8.12	-7.03	-5.35	1.48	-13.82	52.19

Note: Each cell in the upper left 12 matrix gives the relative contribution of each columnar entity to the variance of the row entity's forecast error. The "FROM" column reports the share of the forecast error variance for the entity in the row, attributable to others. It represents the exposure of the entity to the GLSL. The "TO" line reports the total contributions of the entity in the column to the forecast error variance of all other entities and represents the influence of the entity on the GLSL. The "NET" reports each entity's difference between its influence and its exposure. The total connectedness index in the lower right cell is the average of the items in the "TO" row (which is also the average of the "FROM" column), multiplied by 100.

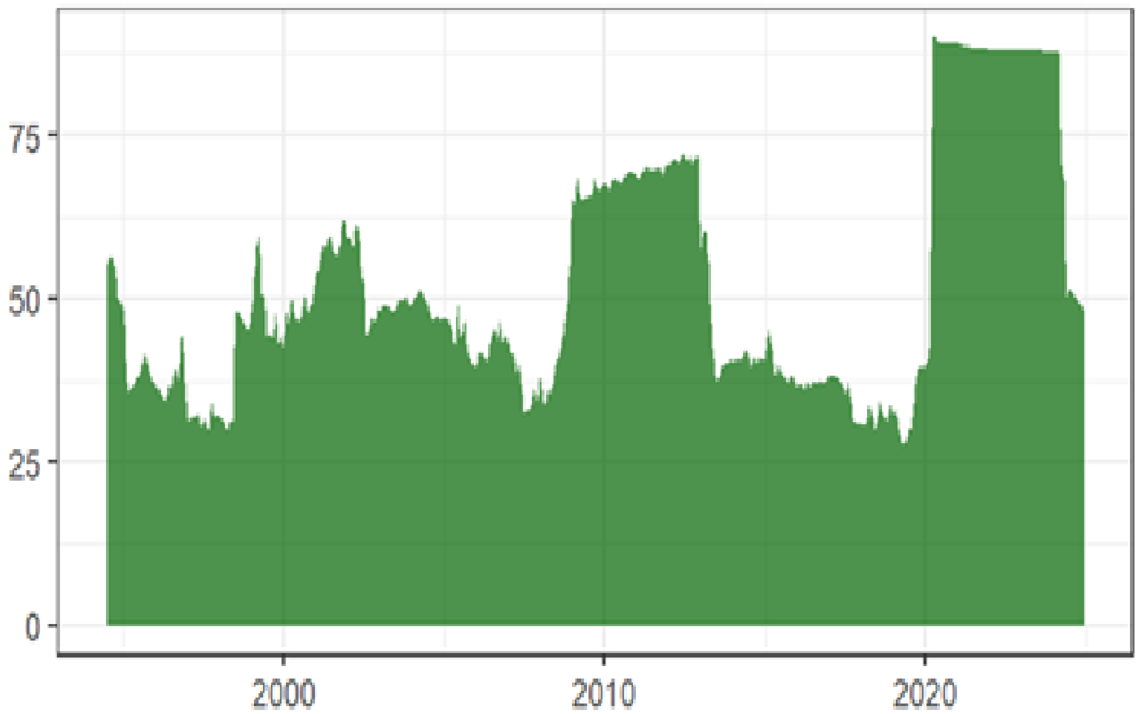

Figure 7: Rolling Sample System-Wide GLSL Economic Connectedness (including other states and provinces).

Note: This graphic presents the evolution of the system-wide economic connectedness of the GLSL region and other states (RUS) and provinces (RCA).

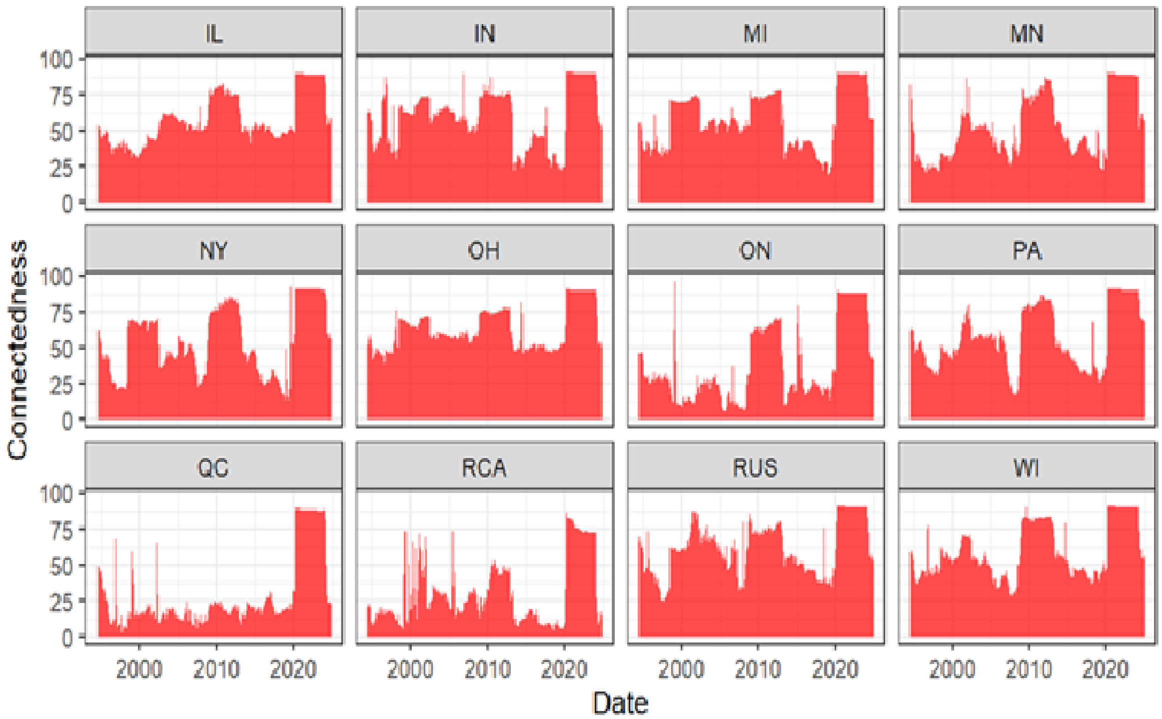

Figure 8: Rolling Sample Connectedness From Others.

Note: This graphic presents the evolution of the connectedness "From" others for each entity in the GLSL region.

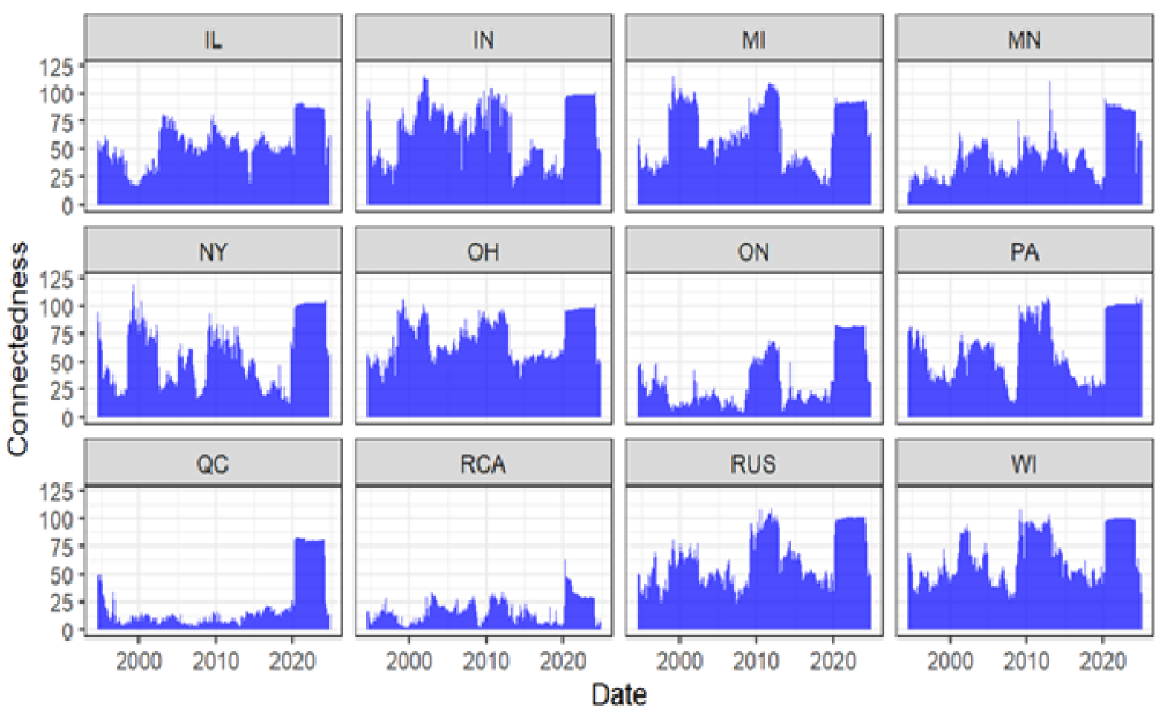

Figure 9: Rolling Sample Connectedness To Others.

Note: This graphic presents the evolution of the connectedness "To" others for each entity in the GLSL region.

Table 3: Descriptive Statistics of Regional Time Series Data

State	Minimum	Maximum	Mean	Std Dev	Skewness	Kurtosis
IL	-0.083	0.028	-0.001	0.008	-3.344	33.193
OH	-0.172	0.077	-0.001	0.012	-6.163	96.983
MN	-0.066	0.011	-0.000	0.005	-5.865	69.105
MI	-0.430	0.252	-0.001	0.028	-7.387	158.055
WI	-0.082	0.015	-0.000	0.006	-7.443	103.540
PA	-0.144	0.044	-0.001	0.008	-12.231	223.401
NY	-0.205	0.054	-0.002	0.011	-13.597	257.352
IN	-0.238	0.094	-0.000	0.014	-9.952	188.530
QC	-0.229	0.104	-0.000	0.019	-3.959	58.985
ON	-0.171	0.085	-0.001	0.015	-3.265	45.963
RUS	-0.095	0.023	-0.001	0.006	-9.910	158.899
RCA	-0.093	0.061	0.000	0.014	-0.475	8.480

Note: This table presents comprehensive descriptive statistics for monthly employment growth rates across ten U.S. states and Canadian provinces.