Super-Connectors: Immigrant Executives and the Architecture of R&D Networks

Yajie Xu
University of South Florida

Kazuma Takakura
University of Maryland

February 1, 2026

[Click here for the most recent version]

Abstract

This paper investigates the micro-foundations of R&D network formation and its impact on firm performance, specifically examining the role of immigrant executives in reducing collaboration frictions. Building upon Cournot competition and network formation game theory, we develop a structural model that captures the trade-off between technology spillovers and product market rivalry. In the first stage, firms form linkages based on a random utility framework; in the second stage, they compete in output level conditional on the formed network. This theoretical framework naturally provides a two-step instrumental variable strategy to address the empirical identification challenge posed by network endogeneity. Using a novel dataset combining firm leadership profiles with R&D activities, we find that the presence of immigrant executives significantly lowers link-specific costs, approximately tripling the odds of forming R&D alliances in the US sample. Furthermore, our analysis reveals asymmetric spillover effects: immigrant-led firms generate substantial positive externalities that enhance the productivity of native-led firms. These findings suggest that diversity in corporate leadership facilitates network densification and efficient knowledge diffusion.

Keywords: R&D Networks, Immigrants, Knowledge Spillover
JEL Codes: D85, O30, J15

1 Introduction

Innovation is the primary engine of modern economic growth, yet firms rarely innovate in isolation. They are embedded in complex networks of research and development (R&D) collaborations where they simultaneously compete for market share and cooperate to share knowledge. The existing literature has robustly established that these R&D networks are not random; they exhibit specific structural features such as sparsity, clustering, and degree heterogeneity (Hanaki et al., 2010; Tomasello et al., 2016). However, while the structural properties of these networks are well-documented, the specific micro-foundations driving the formation of these links, particularly the role of human capital composition in lowering collaboration costs, remain underexplored. This paper bridges that gap by examining how immigrant executives shape the topology of R&D networks and, subsequently, firm performance.

We posit that the formation of R&D alliances is driven by a trade-off between local knowledge spillovers (complementarities) and global product market competition (substitutability), a tension formalized in the work of Bloom et al. (2013) and König et al. (2019). Within this framework, we propose the driving factor of network formation: the immigrant executive. Drawing on Upper Echelons Theory (UET), we argue that immigrant executives possess distinct social capital profiles that reduce information asymmetries and search costs, particularly in cross-border or diverse contexts (Kim and Higgins, 2007; Hambrick and Mason, 1984). By integrating unique data on firm leadership with structural network econometrics, we investigate whether immigrant backgrounds serve as a catalyst for network densification and whether the resulting spillovers yield heterogeneous returns for native versus immigrant-led firms.

To identify these effects, we employ a structural joint model of network formation and economic outcome. Our theoretical framework utilizes a two-stage game similar to Goyal and Moraga-González (2001) and Jackson (2008). In the first stage, firms endogenously form collaboration links based on a random utility framework, where the decision to collaborate depends on the marginal gain in profit versus link-specific costs. In the second stage, conditional on the network formed, firms engage in Cournot competition, choosing optimal output and R&D effort levels. This structure allows us to model the network not as an exogenous fixed matrix, but as an equilibrium outcome of strategic choices subject to idiosyncratic shocks, specifically Type-I extreme value errors, which enable the use of a logistic network formation model (Mele, 2017).

Standard estimates of peer effects are often plagued by the reflection problem and selection bias (Manski, 1993). We overcome this by employing a two-step instrumental variable

(IV) strategy following König et al. (2019). Unlike standard approaches that assume homogeneous peer effects, we extend their work by using a higher-order Spatial Autoregressive (SAR) model that allows for group-level heterogeneity, distinguishing the magnitude of spillovers generated by immigrant-led firms versus native-led firms Hsieh and Lee (2016).

Our empirical analysis yields three distinct contributions. First, extending the work of König et al. (2019), we provide evidence that the presence of immigrant executives significantly lowers the threshold for link formation. Specifically, we find that having an immigrant executive triples the odds of forming an R&D alliance in the US sample, suggesting that diversity is a critical driver of network connectivity. Second, we quantify the economic value of these connections, showing that technology spillovers significantly enhance firm output beyond what internal R&D investment achieves. Finally, we uncover a crucial asymmetry in spillover directions: immigrant-led and foreign firms impart substantial net positive externalities to native-led firms, supporting the "rising tide" hypothesis of globalization in innovation networks.

The remainder of this paper is as follows: Section 2 reviews the literature on R&D cooperation and the role of immigrants. Section 3 outlines the theoretical two-stage game and the micro-foundations of the profit function. Section 4 describes the unique dataset employed in this study. Section 5 outlines the methodology, including the regression models used for analysis. The estimation results are presented in Section 6, followed by the conclusions in Section 7. To maintain clarity and conciseness in the main text, additional materials, including tables with a sample company profile and the proof of the validity of the IV methods for the SAR model, are provided in Section 9.

2 Literature Review

This paper builds on prior work about the impact of immigrants on innovation and R&D networks. In the U.S., skilled immigrants have been playing an important role for the innovation (Ganguli and MacGarvie, 2025; Glennon, 2024). Bernstein et al. (2022) found that while immigrants account for roughly 16% of U.S. inventors, they are responsible for 23% of total innovation output. More importantly, they generate significant positive externalities for their native collaborators. In those processes, networks play a key role. For instance, Chinese and Indian immigrant networks in Silicon Valley have facilitated the extensive clustering of Chinese and Indian high-tech entrepreneurs within a small geographic area (Kerr and Kerr, 2019). Bolzani and Scandura (2024) shows the importance of domestic collaboration networks for innovation in immigrant- and native-owned firms using survey data. We contribute to this literature by adding another empirical evidence from the conmprehensive dataset on the impact of immigrants on innovation and quantifying its importance through the R&D networks.

More broadly, this paper studies the role of collaboration in knowledge spillovers. Akcigit et al. (2018) shows that interactions with better inventors are strongly correlated with researchers' productivity. Zacchia (2020) studied the interactions between individual inventors from different companies that drive knowledge spillovers among firms. In his study, in which he estimated the spillover effects given an exogenous network structure using the microdata of inventors' collaboration, the endogeneity of network formation was not involved in the model. Furthermore, alliances between firms are driven not only by collaboration between inventors, but also by social networks of their top management team (Kim and Higgins, 2007). In our study, we link entrepreneurs' micro-behaviours to firm-level outcomes and formally conceptualize the endogenous network formation process to identify the contribution of immigrant-led firms on knowledge spillovers.

We also contribute to the literature of bridging R&D spillovers and strategic network formation. Bloom et al. (2013) is one of the novel studies on this topic, which has disentangled the degree of R&D spillovers from the negative competition effect against market rivals. König et al. (2019) describes the empirical model that incorporates both R&D spillovers and market competition. They provide a characterization of the Nash equilibrium and structurally estimate the model to quantify the degree of R&D spillovers compared to the market competitiveness. Their model focuses on how R&D networks works based on homogeneous technology spillovers and competition. We extend König et al. (2019) by introducing the network formation stage and heterogeneous knowledge spillovers. We argue that immigrant executives have a lower marginal cost of forming international or diverse links, which alters the equilibrium network structure. Also, we separately quantify the knowledge spillover effects between different pairs of firms. Our empirical results may shed lights on the targeting policy to accelerate innovation.

3 Theoretical Framework

3.1 Two-stage Game Model

We consider a two-stage game with complete information (Goyal and Moraga-González, 2001; Jackson, 2008). Consider a set of firms $\mathcal{K} = \{1, \ldots, k\}$ is partitioned in industries $\mathcal{D} = \{1, \ldots, d\}$. Those firms are producing single-product and they are imperfectly differentiated. We characterize the market as a Cournot competition. As well as the quantity choice in a usual Cournot competition game, firms also conduct R&D to improve their productivity, both solely and jointly. Firm i decides whether to form a collaboration with another firm in the first stage, THE given the equilibrium networks, firm i chooses its output level y_i and R&D effort level e_i in the second stage.

We describe the structure of this game backward. In the second stage, given the collaboration network, firms compete in the Cournot competition market. Assuming that the potential for the goods to be imperfect substitutes, the inverse demand function is expressed as:

$$p_i = \bar{p}_d - y_i - \rho \sum_{j=1}^{k} b_{ij} y_j. \tag{1}$$

Here, $\bar{p}_d$ captures industry variations, while $\rho > 0$ represents the substitutability extent between products. The dummy variable $b_{ij} \in [0, 1]$ is an entry of the matrix B that describes the product market closeness of goods i and j. When goods i and j are substitutable, b_{ij} becomes close to 1 and y_j will influence p_i. Assuming $b_{ii} = 0$, which reflects that a firm's own products do not compete with one another.

We also need to specify the marginal cost. We assume that each firm faces a fixed industry-specific marginal production cost $\bar{c}_d$, and can reduce it by investing in research and development (R&D), representing the R&D effort of firm i as e_i. This cost reduction is not only come from the effect of a firm's own effort ϕ, but is also associated with the spillover effect λ from collaborating firms' efforts. The corresponding marginal cost c_i can be expressed as:

$$c_i = \bar{c}_d - \underbrace{\phi e_i}_{\text{own effort}} - \underbrace{\lambda \sum_{j=1}^{k} a_{ij} e_j}_{\text{spillover}}. \tag{2}$$

Let us define the collaboration matrix A. Each element a_{ij} is a binary dummy variable, which equals to 1 if firm i and j collaborate, and 0 otherwise. Since this relation is reciprocal, $a_{ij} = a_{ji}$. a_{ii} is set to zero to ensure that spillover effects are not confounded with the effects of a firm's own characteristics indicates whether firm i and j collaborate together or not. We set $\mathrm{a}_{ii} = 0$ for all $i = 1, ..., N$, to exclude self-loop.

It's posited that the R&D effort's associated cost (or the R&D investment) increases with effort, displaying diminishing returns, specifically ψ. A network formation cost, γ, is also introduced, which detracts from the profit of firm i and firm j when $a_{ij} = 1$. Consequently, the profit for firm i is

$$\pi_i = \pi_i(y_i, e_i) = (p_i - c_i)y_i - \psi e_i^2 - \sum_{j=1}^{k} a_{ij}\gamma \tag{3}$$

Substituting equations (1) and (2) into (3) gives:

$$\pi_i = -y_i^2 - \psi e_i^2 + \phi y_i e_i + (\bar{p}_d - \bar{c}_d)y_i + \left(-\rho \sum_{j=1}^{k} b_{ij} y_j + \lambda \sum_{j=1}^{k} a_{ij} e_j\right) y_i - \sum_{j=1}^{k} a_{ij}\gamma$$

Optimizing with respect to e_i and y_i yields:

$$e_i = \frac{\phi}{2\psi} y_i \tag{4}$$

$$2y_i = \xi_i - \rho \sum_{j=1}^{k} b_{ij} y_j + \phi e_i + \lambda \sum_{j=1}^{k} a_{ij} e_j \tag{5}$$

where $\xi_i = \bar{p}_d - \bar{c}_d$. We can denote this optimality condition by substituting e_i from equation (4) to (5) without $\mathbf{e}$ such that

$$y_i = \frac{2\psi}{4\psi - \phi^2}\xi_i + \lambda \frac{\phi}{4\psi - \phi^2} \sum_{j=1}^{k} a_{ij} y_j - \rho \frac{2\psi}{4\psi - \phi^2} \sum_{j=1}^{k} b_{ij} y_j, \tag{6}$$

where ψ is sufficiently large, i.e., $4\psi - \phi^2 > 0$.

In the first stage, firm i proposes a collaboration to firm j when the marginal gain from the collaboration is positive. Following the discrete choice random utility framework (McFadden, 1972), we assume that firm i's perceived utility from a network state A is given by $\Pi_i(\mathbf{y}, A) + \varepsilon_{ij}$, where $\Pi_i(\cdot)$ represents the deterministic profit depending on the output levels $\mathbf{y}$ and network structure A, and ε_{ij} captures an idiosyncratic link-specific shock. Given the output levels, the deterministic marginal gain δ_{ij} from establishing a link (i, j) is equivalent for both firms (reciprocity) and is given by:

$$\delta_{ij} = \pi_i(y_i, y_j \mid a_{ij} = 1) - \pi_i(y_i, y_j \mid a_{ij} = 0) = \frac{\phi\lambda}{2\psi} y_i y_j - \gamma + \epsilon_{ij}, \tag{7}$$

where $\epsilon_{ij} = \epsilon_i|\{a_{ij} = 1\} - \epsilon_i|\{a_{ij} = 0\}$. Since cooperation is a reciprocal relationship, the marginal profit gain δ_{ij} of firm i from cooperation with firm j, is the same as the other way around, $\delta_{ij} = \delta_{ji}$. We assume that ε_{ij} follows an identically and independently distributed Type-I extreme value (Gumbel) distribution, following the structural network formation literature (Mele, 2017; Hsieh et al., 2025a). This distribution is chosen because the difference of two independent Gumbel variables follows a logistic distribution, which provides a tractable likelihood function (McFadden, 1972; Anderson et al., 2199). More crucially, this property ensures that the dynamic updating process converges to a unique stationary distribution characterized by an Exponential Random Graph Model (ERGM). The probability that a link is formed follows a logit model:

$$\log\left(\frac{P(a_{ij}=1)}{1-P(a_{ij}=1)}\right) = \vartheta\delta_{ij} = \vartheta\left(\frac{\phi\lambda}{2\psi}y_i y_j - \gamma\right), \tag{8}$$

where ϑ is the inverse noise parameter (or inverse temperature). This parameter governs the rationality of the network formation process: as $\vartheta \to \infty$, the noise vanishes and firms deterministically form links whenever the marginal profit is positive; as $\vartheta \to 0$, economic incentives become irrelevant and link formation becomes purely random (Hsieh et al., 2025b).

3.2 Heterogeneity

To better understand the mechanism, we extend the structural models by introducing 2 types of heterogeneity: pair-wise heterogeneous collaboration costs and group-level heterogeneous spillover and competition effects.

3.2.1 Heterogeneous Collaboration Costs

For each pair of firms, several factors influence the cost of link formation, γ_{ij}. The first determinant is *homophily*; existing studies indicate that similarity between firms facilitates cooperation by generating trust, which lubricates collaboration (Useche et al., 2020). This encompasses geographic proximity and cultural similarities that lower the barriers to interaction and monitoring costs. Furthermore, under very high environmental uncertainty, contractual governance may hamper rather than help alliance performance, as bounded rationality limits the number of contingencies that can be accounted for in a contract Krishnan et al. (2016). Thus trust is particularly critical in strategic alliances to mitigate relational hazards, serving as a substitute for costly, complex contracting in environments characterized by high uncertainty (Kale et al., 2004; Rezaei, 2011).

Furthermore, consistent with the Upper Echelons Theory, it is not merely firms but specific executives who interpret strategic situations and make alliance decisions based on their own cognitive bases and social capital (Hambrick and Mason, 1984). Consequently, executive characteristics, specifically immigrant status, significantly influence network formation by altering the topology of search and reducing transaction costs (Levina and Kane, 2009). Immigrant executives possess "dual embeddedness," meaning they are simultaneously integrated into the institutional environment of the host country and the social networks of their home country (Brzozowski and Cucculelli, 2020).

This dual positioning allows immigrant executives to act as "knowledge brokers" who bridge structural holes between disconnected markets, thereby reducing the information asymmetry and search frictions associated with finding partners (Lin et al., 2019). While co-ethnic networks allow for rapid alliance formation through identification-based trust, immigrant executives also lower the psychological and transaction costs of forming ties with dissimilar firms to access non-redundant resources. Thus, we extend the link formation cost function γ_{ij} to account for these reductions in search and monitoring costs facilitated by the executive's specific network position.

3.2.2 Heterogeneous Spillover and Competition Effects

To understand the heterogeneous spillover and competitive effects within and across different types of firms, we divide them into n_g subgroups. Then the collaboration network A can be divided into $n_g \times n_g$ blocks:

$$A = \begin{bmatrix} A^{g_1 g_1} & A^{g_1 g_2} & \cdots & A^{g_1 g_n} \\ A^{g_2 g_1} & A^{g_2 g_2} & \cdots & A^{g_2 g_n} \\ \vdots & \vdots & \ddots & \vdots \\ A^{g_n g_1} & A^{g_n g_2} & \cdots & A^{g_n g_n} \end{bmatrix}, \tag{9}$$

where A^{gh} represents the matrix of links between groups g and h. The corresponding heterogeneous spillover effects can be expressed as λ_{gh}. In the same vein, the competition matrix B can also be partitioned according to the groups, and heterogeneity in ρ_{gh} captures the competition environment rather than their product characteristics.

Allowing for the heterogeneity in the results of the previous section, the optimal R&D effort and network formation condition is expressed in the following two equations:

$$y_i = \frac{2\psi}{4\psi - \phi^2}\xi_i + \frac{\phi}{4\psi - \phi^2} \sum_{\substack{j=1 \\ i \in g, j \in h}}^{k} \lambda_{gh} a_{ij} y_j - \frac{2\psi}{4\psi - \phi^2} \sum_{\substack{j=1 \\ i \in g, j \in h}}^{k} \rho_{gh} b_{ij} y_j, \tag{10}$$

$$\log\left(\frac{P(a_{ij}=1)}{1-P(a_{ij}=1)}\right) = \vartheta\left(\frac{\phi\lambda_{gh}}{2\psi} y_i y_j - \gamma_{ij}\right), \quad \text{for } i \in g, j \in h. \tag{11}$$

4 Data

4.1 R&D Networks, M&A, and Balance Sheet Information

The R&D alliances from 2003 to 2022 are obtained from the SDC Joint Ventures & Strategic Alliances Database (König et al. (2019);Schilling (2009)). This database is chosen for its comprehensive collection of inter-firm R&D cooperation, sourced from an extensive range of resources, including SEC filings, international equivalents, trade publications, and various news sources. The worldwide coverage enables the study to investigate the roles of immigrants in forming international collaborations and distinguish the heterogeneous spillover effects across US-immigrant-led, US-native-led, and foreign companies. To focus on innovative activities, only the alliances explicitly classified as R&D collaboration are collected.

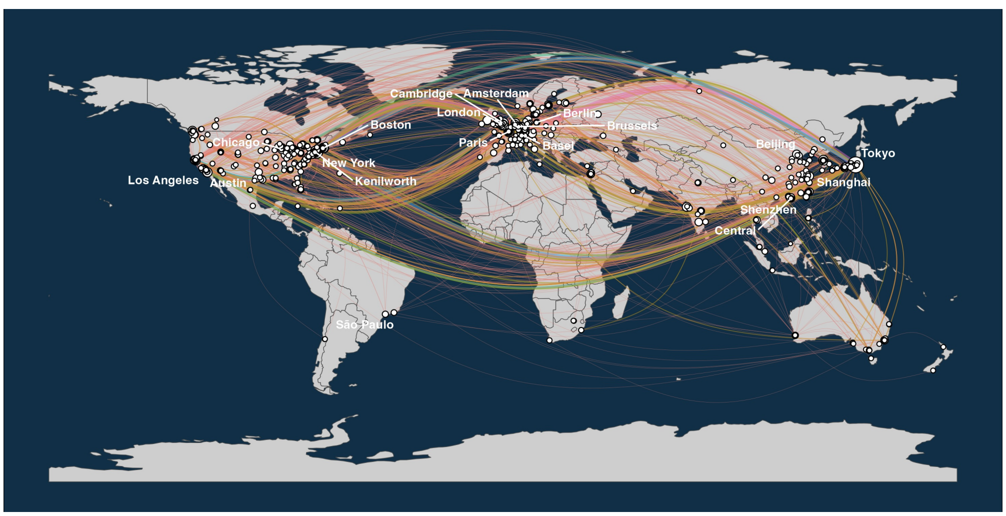

Figure 1: City-level map of firms and collaborators, with node size reflecting degree centrality.

Over the past two decades, some firms underwent mergers. Following the approach in König et al. (2019), it is assumed that acquiring firms inherit all the R&D collaborations of the target firms. To compile a comprehensive dataset on mergers and acquisitions (M&A), information was sourced from Thomson Reuters' SDC M&A and S&P Compustat databases, while financial data was obtained from S&P Compustat and Financial Modeling Prep.

Initially, there were 8,383 alliances in the dataset. After filtering out non-public firms[1], firms that had been acquired, firms that went bankrupt, and firms without R&D expenditure, as well as excluding alliances that subsequently involved only a single firm, the final sample comprised 1,448 alliances globally and 878 within the U.S., involving 1,086 firms worldwide and 363 U.S. firms. Figure 1 presents the city-level locations of all firms, with the size of each node representing degree centrality, and several key hub cities labeled. For a breakdown of the number of firms across different regions, see Table 7.

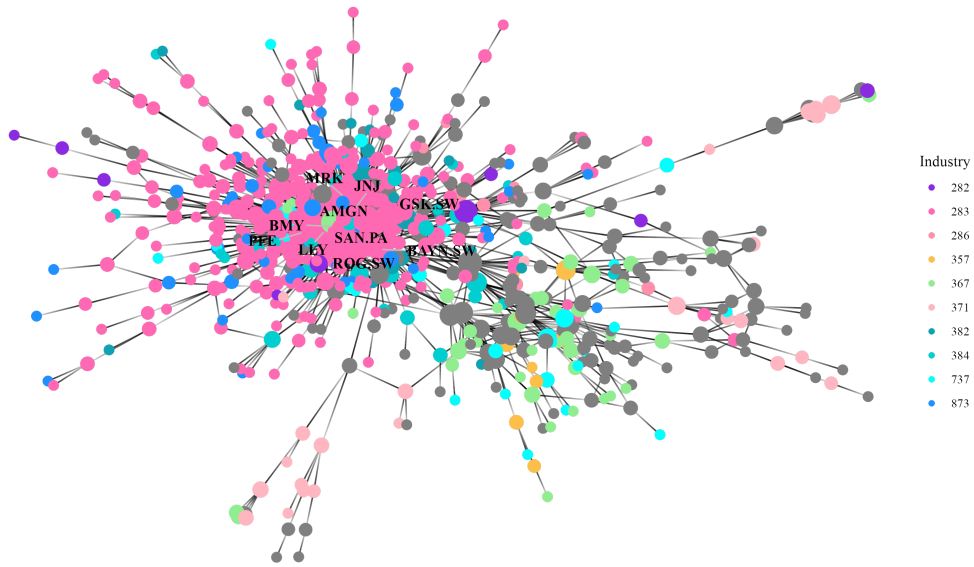

Figure 2: The largest component of the accumulated R&D networks until 2022. Node colors represent sectors based on 3-digit SIC codes, while node sizes reflect the number of collaborations for each firm.

Figure 2 presents the largest connected component of the accumulated R&D collaboration network of the glable sample. There's a total of 695 firms. Nodes' size is proportion to the degree centrality and color indicates the industry. The top 10 firms in terms of the highest degree of centrality are labeled, in which most of them are US firms, and all of them are in the drugs industry. Detailed information regarding these leading 10 firms is outlined in Table 1. The nodes' color reflects the industry, almost all of them are high-tech. About one-half of firms are in the drugs (SIC: 283) sector. The Research, Development, and Testing Services (SIC: 873) and Electronic Components and Accessories (SIC: 367) are the top 2 and 3 industries.

Figure 3 illustrates the overall trends of newly formed networks for both the global and U.S. samples from 2003 to 2022. The left panel displays the number of participants in

[1]According to Bloom et al. (2013), R&D activities are predominantly concentrated among public firms, thus the sample captures the majority of innovation efforts.

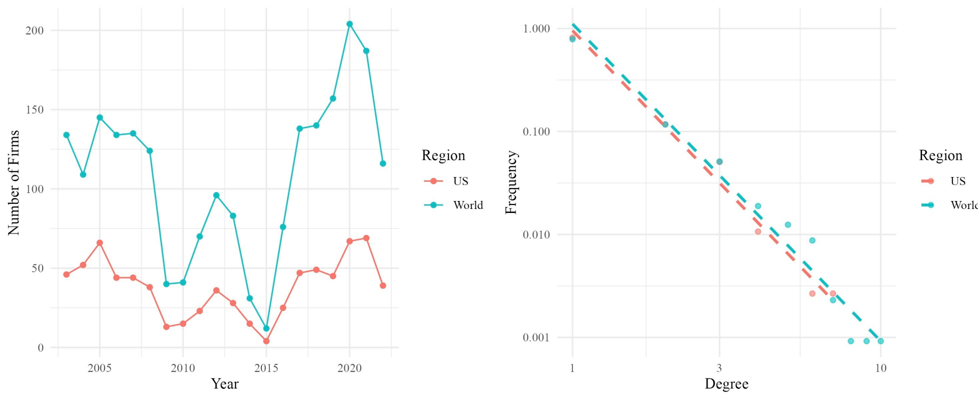

Figure 3: Descriptive statistics of newly formed alliances from 2003 to 2022. The left panel shows the number of participants in newly established alliances over time, revealing similar trends in both global and U.S. samples. The right panel displays the logarithmic degree distribution, with the linearity of the fitted lines indicating that degree centrality follows a power-law distribution.

Table 1: Top 10 Firms Ranked by Degree Centrality in the Largest Component

Rank	Name	Symbol	Region	SIC	Industry	Degree
1	Merck Co., Inc.	MRK	United States	283	Drugs	59
2	Roche Holding AG	ROG.SW	Switzerland	283	Drugs	52
3	Pfizer Inc.	PFE	United States	283	Drugs	46
4	Johnson Johnson	JNJ	United States	283	Drugs	37
5	Bristol-Myers Squibb Company	BMY	United States	283	Drugs	35
6	GlaxoSmithKline plc	GSK.SW	United Kingdom	283	Drugs	34
7	Eli Lilly and Company	LLY	United States	283	Drugs	32
8	Bayer Aktiengesellschaft	BAYN.SW	Germany	283	Drugs	30
9	Amgen Inc.	AMGN	United States	283	Drugs	29
10	Sanofi	SAN.PA	France	283	Drugs	28

newly established alliances over time, showing that both samples exhibit similar patterns. On average, approximately 130 firms join new collaborations each year. Notably, there are significant declines around 2009, 2015, and 2021, corresponding to major economic disruptions: the 2008 financial crisis, the surge in mega-mergers in 2014[2], and the COVID-19 pandemic. These events resulted in ongoing economic uncertainty, influencing global markets and investment in R&D. The tech sector, in particular, experienced waves of mergers and acquisitions during these periods, as firms aimed to consolidate and strengthen their positions in emerging technologies, potentially leading to a reduction in R&D collaborations as companies prioritized internal integration and the protection of proprietary technologies.

[2]Emily Liner's blog on The Harvard Law School Forum on Corporate Governance discusses the key factors driving the 2014 M&A surge. See: https://corpgov.law.harvard.edu/2016/03/16/whats-behind-the-all-time-high-in-ma/.

The right panel shows the logarithmic degree distribution, which is highly skewed. The linearity of the fitted lines suggests that the degree centrality follows a power-law distribution, indicating that the networks are typically sparse, with most firms participating in only a single collaboration, while a small number of firms are highly active in forming new alliances. This pattern aligns with Figure 2, which shows that pharmaceutical companies are frequently involved in such collaborations. The development of new drugs often requires long timelines, substantial funding, and involves considerable risk, leading these firms to collaborate more frequently to pool resources and mitigate risk.

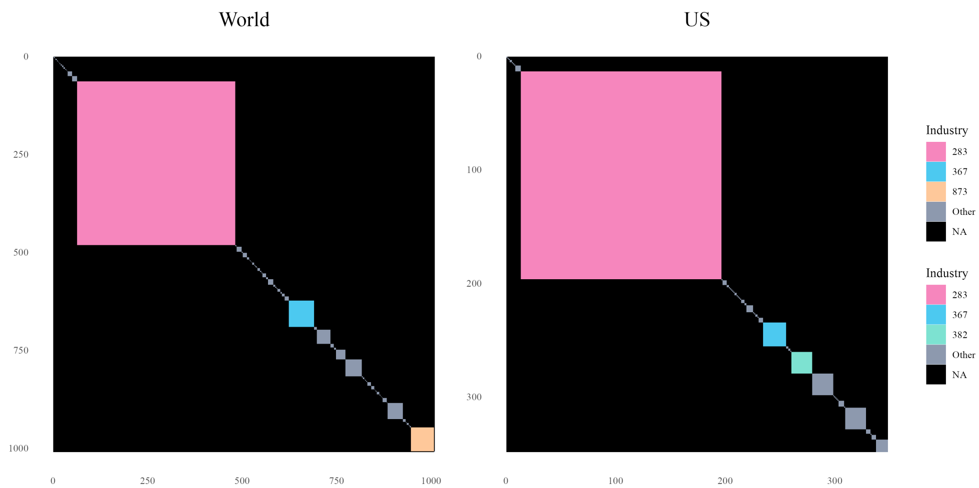

Figure 4: The competition matrices $\mathbf{B}$, measured at the 3-digit industry SIC code level, highlight the top three industries based on the number of firms. The corresponding SIC codes are displayed on the left.

Table 2: Top 5 Industries

Industry	**3-digit SIC**	**Count**	**Rank**
World			
Drugs	283	418	1
Electronic Components and Accessories	367	67	2
Research, Development, and Testing Services	873	61	3
Surgical, Medical, and Dental Instruments and Supplies	384	43	4
Computer Programming, Data Processing, and Other Computer Related Services	737	41	5
US			
Drugs	283	183	1
Electronic Components and Accessories	367	21	2
Laboratory Apparatus and Analytical, Optical, Measuring, and Controlling Instruments	382	19	3
Surgical, Medical, and Dental Instruments and Supplies	384	19	4
Computer Programming, Data Processing, and Other Computer Related Services	737	19	5

Notes: This table presents the top five industries, ranked by the number of firms, for both the global and U.S. samples. Both samples exhibit a similar pattern, with the pharmaceutical industry and IT-related sectors dominating participation in R&D collaborations.

4.2 Entrepreneurs' Demographic Information

Entrepreneurs in this study are defined as the senior executive officers of the firms. To gather information about these individuals, the primary source is the annual reports filed with the Securities and Exchange Commission (SEC), which provide names and brief biographies of the relevant individuals. This information is further enriched by cross-referencing with firms' official websites, Wikipedia, LinkedIn, WikiTree, Bloomberg, Encyclopedia.com, NNDB, WBE, and various news reports.

Due to the occasional unavailability of explicit birthplace information, an inferential approach is adopted. The location of the universities where these entrepreneurs obtained their bachelor's degrees serves as a proxy for inferring their birthplace (Mahroum and Ansari (2017)). Entrepreneurs who obtained their degrees outside the country where their firm is located are classified as immigrants. Since some immigrants may arrive young and enroll in U.S. universities before they launch their careers, Our analysis would not count them as immigrants, therefore our estimates can be considered a lower bound on immigrants' contribution to U.S. executive leadership. The born regions for all executives can be found in Table 8.

To focus on the influence of U.S. immigrants, all the executives of the non-US firms are assumed born in the country where their firm is located. There are also some supportive reasons for this assumption: first, compared to other countries, immigrant executives are much more prevalent in the U.S., particularly in sectors like technology and healthcare (Mahroum and Ansari (2017)), which are the main sectors for the research sample. This is because the U.S. has a more diverse and immigrant-friendly environment, while other countries, such as in Asia and Africa, tend to hire local executives, either due to cultural and linguistic preferences or more restrictive immigrant policies (Arp et al., 2013; Platonova and Urso, 2013; Flahaux and De Haas, 2016). In Europe, while other is movement between countries, cultural similarities often limit the diversity in executive positions. Furthermore, researches show that European countries, compared to the U.S., had less attractive policies for highly skilled immigrants and experienced net emigration, resulting in a 'brain drain' to the U.S.(Mahroum, 1999, 2000, 2001; Prato, 2022).

4.3 Summary Statistics

Table 3 provides summary statistics for all the variables used in this research. The R&D effort is quantified by the logarithm of R&D expenditure. Collaborator's R&D efforts are measured by the sum of the efforts of a firm's collaborators within the year, while competitors' R&D efforts are captured by the total R&D expenditure of firms that share the same 3-digit

Table 3: Summary Statistics

	Mean	SD	Median	Min	Max	N
World						
Output	19.63	7.61	21.43	0.00	33.34	15,844
Productivity	18.85	4.98	19.79	0.00	30.57	15,322
Collaborators' Productivity	13.09	33.59	0.00	0.00	541.75	19,703
Competitors' Productivity	2,459.11	2,525.77	862.20	0.00	7,037.76	19,703
R&D effort	13.44	7.87	16.72	0.00	30.73	15,844
Immigrant Dummy	0.13	0.34	0.00	0.00	1.00	19,703
US						
Output	16.62	7.21	18.29	0.00	26.97	5,209
Productivity	19.81	3.82	20.07	0.00	30.57	5,063
Collaborators' Productivity	13.99	38.85	0.00	0.00	541.75	6,878
Competitors' Productivity	3,002.28	2,557.04	3,362.15	0.00	7,037.76	6,878
R&D effort	16.60	5.10	17.53	0.00	30.73	5,209
Immigrant Dummy	0.38	0.49	0.00	0.00	1.00	6,878
Female Dummy	0.06	0.13	0.00	0.00	1.00	6,878
Proportion of Executives with Their Highest Degree						
No Degree	0.00	0.03	0.00	0.00	0.33	6,878
Bachelor	0.16	0.23	0.00	0.00	1.00	6,878
Master	0.23	0.27	0.14	0.00	1.00	6,878
Doctor	0.20	0.26	0.00	0.00	1.00	6,878

Notes: All financial data are deflated by the CPI and converted to U.S. dollars. Output is the logarithm of revenue from annual reports, R&D effort is the logarithm of R&D expenditure, and productivity is time-lagged R&D capital stocks with a 15% depreciation rate. ipoYear refers to the year of a company's first public stock offering. The immigrant dummy equals one if a firm has at least one immigrant executive in a year, and zero otherwise. Foreign firms are assumed to have no immigrant executives. The female dummy equals one if at least one female executive is present, and zero otherwise.The last four variables represent the proportion of executives with the highest academic degrees, counting only the highest degree held. For example, a Ph.D. is counted as a doctorate, not a bachelor's degree.

SIC code, hence identified as competitors. Productivity is assessed using the one-year-lagged R&D capital stock, which is calculated through the perpetual inventory method based on the firm's R&D expenditures with a 15% depreciation rate Bloom et al. (2013).

All financial data are reported in U.S. dollars, with currency translation rates obtained from The World Bank Group and Fiscal Data. To account for the effects of inflation, and given that not all countries provide Producer Price Index (PPI) data annually, the financial data are deflated using the annual average Consumer Price Index (CPI), generally based on the Laspeyres formula. The primary source for CPI data is The World Bank Group. However, CPI data for Taiwan, the European zones, and Russia in 2022 were not available through this source and were instead obtained from National Statistics, Republic of China (Taiwan), the European Central Bank, and Trading Economics, respectively.

For the U.S. sample, demographic information on executives is collected. At the firm level, The immigrant dummy variable is set to one if there is at least one immigrant executive in the given year, and zero otherwise. Similarly, the female dummy variable is set to one if there is at least one female executive, and zero otherwise. The last four variables quantify the proportion of executives holding the highest academic degrees. For instance, if a CEO possesses both a Ph.D. and a master's degree, the count of doctorate degree holders increases by one, but the count of master's degree holders does not.

5 Identification Strategy

In this section, we specify the econometric model for equations (10) and (11) (and normalizing $\psi = \frac{1}{2}$ and $\phi = 1$) for empirical analysis for panel data over time periods $\mathcal{T} = \{1, \ldots, t\}$. For each firm i at time t, the outcome is a total output y_{it}. The k_t-dimensional vectors $\mathbf{y}_t = (y_{1t}, y_{2t}, \ldots, y_{kt})'$ summarize the outcome variables of k_t firms. Let $\mathbf{x}_{it}$ be a r-dimensional row vector containing firm i's exogenous characteristics, and let the $k_t \times r$ dimensional matrix $\mathbf{X}_t$ be a collection of such vectors at time t. We capture the dynamic cooperation networks of firms by t-dimension vector $\mathbf{A} = (A_1, A_2, \ldots, A_t)$, where each A_t is a $k_t \times k_t$ adjacency matrix, where each entry $a_{ij,t}$ is a binary indicator which equals one if firm i and j announced an R&D alliance at time t, and zero otherwise. The diagonal of the adjacency matrix is set to zero to ensure that spillover effects are not confounded with the effects of a firm's own characteristics. Similarly, the matrix $\mathbf{B}$ captures product market competition, where each entry B_{ij} equals 1 if firms i and j operate in the same 3-digit SIC industry, and 0 otherwise. The full competition matrix $\mathbf{B}$ is shown in Figure 4, and Table 2 provides descriptions of the five largest industries in our sample.

5.1 Spatial Auto Regression (SAR) Model

In year t, a firm's idiosyncratic fixed marinal production cost $\bar{c}_{it} = \bar{c}_d + \bar{c}_t - \beta X_{it} - v_{it}$, where $\bar{c}_t$ capture the time-specific market shock, vector X_{it} captures the chacartreisitcs can reduce the cost, such as .... and v_{it} represents the unobsevables that can influce the cost. Then in year t, the inverse demand in equation (1) is:

$$p_{it} = \bar{p}_d + \bar{p}_t - y_{it} - \sum_{\substack{j=1 \\ i\in g, j\in h}}^{k} \rho_{gh} b_{ij} y_{jt}, \tag{12}$$

where $\bar{p}_t$ capture the market shocks to the price in year t, then then $\xi_i = \bar{p}_d + \bar{p}_t - \bar{c}_{it} = \beta X_{it} + \bar{p}_d + \bar{p}_t - \bar{c}_d - \bar{c}_t + v_{it}$. Equation (10) can be specified as:

$$y_{it} = \beta X_{it} + \sum_{\substack{j=1 \\ i\in g, j\in h}}^{k} \lambda_{gh} a_{ijt} y_j - \sum_{\substack{j=1 \\ i\in g, j\in h}}^{k} \rho_{gh} b_{ij} y_j + \eta_d + \tau_t + v_{it}, \tag{13}$$

where $\eta_d = \bar{p}_d - \bar{c}_d$ and $\tau_t = \bar{p}_t - \bar{c}_t$.

To investigate the influence of immigrant senior executives and global cooperation, we specify the group g follows this rule: immigrant-led (m), native-led (n), and foreign (f) firms. Specifically, foreign firms are defined as non-US firms. Both immigrant and native firms are located in the U.S.; a firm is classified as immigrant-led if at least one senior executive is an immigrant, and as native-led if none of the senior executives are immigrants. This classification for U.S. firms may vary over the years due to changes in the composition of executive officers, while the classification of foreign firms remains the same. Since we want to understand the influence of immigrants on the global influence, and also want to focus on the situation within the US. In the global sample, we have three groups; in the US sample, we only have 2 groups, m and n. In vector form, the SAR model for the whole sample can be specified as:

$$\begin{aligned}
\mathbf{y}_t &= \mathbf{W}_t(\Theta)\mathbf{y}_t + \mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\eta} + \boldsymbol{\ell}\tau_t + \mathbf{V}_t, \qquad (14)\\
\mathbf{V}_t &\sim i.i.d.\mathcal{N}(0, \sigma^2\mathbf{I}_{kt}), \quad t = 1, \ldots, T,\\
\mathbf{W}_t(\Theta) &= \mathbf{A}_t(\Lambda) + \mathbf{B}(\mathrm{P})\\
&= \begin{bmatrix} \lambda_{mm}A_t^{mm} & \lambda_{mn}A_t^{mn} & \lambda_{mf}A_t^{mf} \\ \lambda_{nm}A_t^{nm} & \lambda_{nn}A_t^{nn} & \lambda_{nf}A_t^{nf} \\ \lambda_{fm}A_t^{fm} & \lambda_{fn}A_t^{fn} & \lambda_{ff}A_t^{ff} \end{bmatrix} + \begin{bmatrix} \rho_{mm}B^{mm} & \rho_{mn}B^{mn} & \rho_{mf}B^{mf} \\ \rho_{nm}B^{nm} & \rho_{nn}B^{nn} & \rho_{nf}B^{nf} \\ \rho_{fm}B^{fm} & \rho_{fn}B^{fn} & \rho_{ff}B^{ff} \end{bmatrix},
\end{aligned}$$

with $\boldsymbol{\eta}$ a d_t-dimensional vector, and $\boldsymbol{\ell}$ a k_t-dimensional vector of ones; $\mathcal{N}$ represents a multivariate normal distribution of dimension k_t, and $\mathbf{I}_{kt}$ is a k_t-dimension identity matrix. It is important to note that the interpretations of λ_{gh} and λ_{hg} differ. For example. λ_{nm} quantifies the average effects from immigrant-led to native-led firms, whereas λ_{mn} measures the effects from native-led to immigrant-led firms. The meaning of for each ρ_{gh} follows a similar logic.

5.2 Network Formation Model

In the network formation process, the link-specific cost is specified as $\gamma_{ijt} = \gamma_0 + \gamma_t - \mathbf{\Gamma}'_{ijt}\boldsymbol{\psi}$. Here, γ_0 captures the baseline cost of collaboration, and γ_t represents time-variant structural costs common to all firms (e.g., macroeconomic conditions). The term $\mathbf{\Gamma}_{ijt}$ is a k_c-dimensional vector of dyadic characteristics, such as executive demographics and homophily measures, that reduce the effective cost of link formation. Then equation (11) can be specified as:

$$\log\left(\frac{P(a_{ij}=1)}{1-P(a_{ij}=1)}\right) = \vartheta(\lambda_{gh}y_iy_j + \mathbf{\Gamma}_{ijt}\boldsymbol{\psi} - \gamma_0 - \gamma_t), \quad \text{for } i \in g, j \in h. \tag{15}$$

In this study, the vector of regressors $\mathbf{\Gamma}_{ijt}$ is specified to capture three distinct drivers of network formation: executive demographics, network structural dependence, and homophily. First, we account for executive demographics by including the binary indicators $\mathit{Immigrant}_t$ and Female_t, which take the value of 1 if at least one firm in the pair (i, j) employs immigrant or female executives in year t, respectively, and 0 otherwise. Second, we model endogenous network structural effects. To capture relationship persistence, we include the binary variable $\mathit{PriorTie}_{ijt}$, which equals 1 if firms i and j have formed an R&D alliance in any year prior to t. To capture triadic closure mechanisms, we include $\mathit{SharedPartner}_{ijt}$, which equals 1 if the firm pair has shared a common alliance partner prior to or during year t.

Third, we examine homophily—the tendency for firms to collaborate with similar partners—measured using the absolute difference between firm attributes, $|x_{it} - x_{jt}|$. In this framework, a negative coefficient suggests that firms with similar characteristics are more likely to partner. We capture social ties using $\mathit{SameOrigin}_{ijt}$ and $\mathit{SameUniversity}_{ijt}$, which equal 1 if at least one pair of executives across firms i and j share the same country of birth or graduated from the same university, respectively. Geographic and industrial proximity are captured by $\mathit{SameCity}_{ij}$ and $\mathit{SameIndustry}_{ij}$. Operational differences are measured by variables denoted with the prefix *Diff*, such as $\mathit{DiffOutput}_{ij,t-1}$, $\mathit{DiffEffort}_{ij,t-1}$, and $\mathit{DiffProd}_{ij,t-1}$, representing the disparity in output levels, R&D effort, and productivity, respectively, in the previous fiscal year. Finally, we control for human capital differences using variables $\mathit{DiffEduB}_{ijt}$ and $\mathit{DiffEduG}_{ijt}$, which measure the absolute difference in the proportion of executives holding a bachelor's and graduate (including master's and doctoral) degree between the two firms.

6 Results

6.1 Spatial Auto Regression (SAR) Model

Table 4 presents the estimation results for the world sample. The first four models explore the overall externalities of cooperation and competition, while the last three models provide finer-grained details by examining heterogeneous peer effects across three types of firms. Model (1) serves as the baseline and does not include any controls or fixed effects. The subsequent models all incorporate both year and industry fixed effects, captured by the 3-digit SIC code. Models (2) and (5) use the original observation, denoted as $\mathbf{W} \times \mathbf{y}$, while Models (3) and (6) utilize $\mathbf{W} \times \mathbf{X}$ as the IV. Finally, Models (4) and (7) employ $\hat{\mathbf{W}} \times \mathbf{X}$ as the IV.

The overall technology spillover effects λ are significant across all models, suggesting that firms' research efforts are positively influenced by their collaborators' efforts. This may indicate that collaborative firms share resources, information, and reduce innovation risks, fostering a robust ecosystem for research and innovation. Before adding fixed effects, ρ is significant but its sign is misaligned with expectations, indicating an upward bias. After accounting for time and firm-specific influences, the true impact of rivals' R&D efforts emerges. The negative sign of ρ reflects the intense competition in the research race, potentially due to limited market resources such as capital and talent. Notably, the magnitude of spillover effects surpasses that of competition effects, suggesting that despite resource competition, firms with more active collaborators are likely to be more confident and ambitious in innovation.

Upon disaggregating the homogeneous effect into distinct categories, it becomes clear that immigrant-led firms make a substantial contribution to native-led firms. Given that the variables are expressed in logarithmic form, the coefficient $\lambda_{nm} = 0.4$ indicates that a one percent increase in R&D spending by immigrant-led firms leads to a 0.4% increase in the output of native-led firms. This significant impact is largely due to the prominent presence of immigrants within influential firms, especially in critical sectors such as pharmaceuticals and information technology.

This trend is consistent with historical patterns. In the 19th century, factors like political and economic instability in Europe, religious and political persecution, and a high demand for skilled labor in the U.S., combined with the freedom and opportunities offered by the country, made the U.S. a prime destination for European scientists and entrepreneurs. Prominent examples include pharmaceutical and chemical companies such as Pfizer, Merck & Co., and DuPont, all founded by immigrants. Following World War II, the U.S. continued to attract global talent, supported by substantial government funding and leading research institutions

Table 4: Regression Results of the SAR Model (World)

	Homogeneous Spillover				Heterogeneous Spillover		
	Exo Net (1)	Exo Net (2)	IV (Exo Net) (3)	2IV (Endo Net) (4)	Exo Net (5)	IV (Exo Net) (6)	2IV (Endo Net) (7)
λ	.0398***	.0296***	.0303***	.0470***			
	(.0015)	(.0024)	(.0014)	(.0028)			
λ_{mm}					.0416***	.0407***	.0293
					(.0065)	(.0072)	(.0359)
λ_{mn}					.0338***	.0393***	-.0811
					(.0094)	(.0138)	(.1949)
λ_{mf}					.0299***	.0306***	.0856**
					(.0040)	(.0044)	(.0429)
λ_{nm}					.0670***	.0662***	.4237***
					(.0074)	(.0113)	(.1093)
λ_{nn}					.0401*	.0456**	.3249***
					(.0206)	(.0216)	(.1178)
λ_{nf}					.0206***	.0225***	-.1663***
					(.0046)	(.0069)	(.0556)
λ_{fm}					.0270***	.0273***	.0841***
					(.0037)	(.0051)	(.0318)
λ_{fn}					.0288***	.0272***	-.0592
					(.0065)	(.0097)	(.0622)
λ_{ff}					.0221***	.0230***	.0308
					(.0030)	(.0027)	(.0244)
ρ	-.0010***	-.0005***	-.0004***	-.0003***			
	(.0000)	(.0001)	(.0001)	(.0001)			
ρ_{mm}					.0045***	.0045***	.0020
					(.0009)	(.0009)	(.0033)
ρ_{mn}					.0013	.0019	-.0026
					(.0021)	(.0022)	(.0103)
ρ_{mf}					-.0036***	-.0034***	-.0010
					(.0008)	(.0007)	(.0033)
ρ_{nm}					.0036**	.0034***	-.0151***
					(.0013)	(.0010)	(.0047)
ρ_{nn}					-.0060	-.0020	-.0550***
					(.0044)	(.0023)	(.0129)
ρ_{nf}					-.0025*	-.0029***	.0143***
					(.0012)	(.0007)	(.0043)
ρ_{fm}					.0020***	.0007	.0030
					(.0007)	(.0007)	(.0025)
ρ_{fn}					.0076***	.0049***	.0157**
					(.0013)	(.0016)	(.0067)
ρ_{ff}					-.0029***	-.0015***	-.0037
					(.0008)	(.0006)	(.0025)
β_p		.3760***	.3748***	.3544***	.3660***	.3646***	.3538***
		(.0224)	(.0135)	(.0139)	(.0222)	(.0128)	(.0148)
β_e		-.0843***	-.0845***	-.0926***	-.0365***	-.0370***	-.0477***
		(.0120)	(.0082)	(.0083)	(.0103)	(.0078)	(.0090)
Intercept	21.3793***	13.6288***	13.7167***	14.3597***	12.7145***	13.0053***	13.6024***
	(.0795)	(2.4103)	(2.4103)	(2.4247)	(2.2796)	(2.2824)	(2.5971)
Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
R^2	.1385	.3945	.3944	.3878	.4604	.4597	.3499
$Adj.R^2$	.1384	.3892	.3892	.3825	.4552	.4545	.3436
$Num.obs.$	15844	15322	15322	15322	15322	15322	15322

*Notes: The dependent variable is the logarithm of the firm's output level. Fixed effects include both time and industry fixed effects. Standard errors are shown in parentheses. Significance levels are indicated as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The parameter λ measures the technology spillover effects, while ρ captures substitution effects. Subscripts on these parameters indicate interactions across different groups; for example, λ_{mn} quantifies the spillover from immigrant-led to native-led firms. β_p represents the productivity impact, measured by the logarithm of lagged R&D stock, and β_e quantifies the effect of effort level, also in logarithmic terms, represented by R&D expenditure.*

like Stanford University and the University of California system. This influx contributed to creating a fertile environment for technological innovation, especially in the Information and Communications Technology sector, reflecting a longstanding tradition of leveraging immigrant expertise to enhance domestic capabilities and drive sectoral growth (Arkolakis et al. (2020)).

The Immigration and Naturalization Act of 1965, which eliminated nationality-based quotas, along with subsequent favorable policies for venture capital and tech entrepreneurship, greatly facilitated the development of Silicon Valley. This region attracted a diverse and highly skilled immigrant workforce, contributing significantly to its growth and innovation (Wadhwa et al. (2007)). Today, many leading U.S. firms, from those established in the historical context of the healthcare sector to those emerging during the digital revolution in Silicon Valley, have been shaped by the active involvement of immigrants in their establishment and ongoing success. These firms bring extensive networks, resources, and experience, influencing local firms through substantial technology spillover.

Additionally, in Model (6), the positive significance of λ_{mf} and λ_{nf} illustrates how foreign firms encourage innovation efforts among U.S. firms, highlighting the beneficial impacts of globalization and the importance of international cooperation. Recalling the link formation model, both IM and $SameBorn$ showed significant positive effects, indicating the crucial role of immigrants in fostering international collaborations and stimulating innovations, which also yield advantages for local U.S. firms. Furthermore, the positive and significant λ_{fm} suggests that collaborations between immigrant and foreign firms are mutually beneficial for innovation.

Table 5: Regression Results of the SAR Model (US)

	Homogeneous Spillover				Heterogeneous Spillover		
	Exo Net (1)	Exo Net (2)	IV (Exo Net) (3)	2IV (Endo Net) (4)	Exo Net (5)	IV (Exo Net) (6)	2IV (Endo Net) (7)
λ	.0469***	.0331***	.0338***	.0551***			
	(.0020)	(.0041)	(.0019)	(.0047)			
λ_{mm}					.0596***	.0593***	.0893***
					(.0087)	(.0061)	(.0242)
λ_{mn}					.0563***	.0648***	.1931**
					(.0118)	(.0127)	(.0783)
λ_{nm}					.0705***	.0713***	.2036***
					(.0074)	(.0103)	(.0543)
λ_{nn}					.0653***	.0739***	.1609
					(.0215)	(.0206)	(.1042)
ρ	-.0012***	-.0004**	-.0004***	-.0003*			
	(.0000)	(.0002)	(.0002)	(.0002)			
ρ_{mm}					.0009	.0010	.0016**
					(.0009)	(.0007)	(.0007)
ρ_{mn}					-.0051*	-.0050***	-.0055***
					(.0029)	(.0016)	(.0018)
ρ_{nm}					.0007	-.0002	.0005
					(.0011)	(.0007)	(.0009)
ρ_{nn}					-.0074**	-.0056***	-.0064***
					(.0029)	(.0017)	(.0020)
β_p		.2927***	.2912***	.2310***	.2973***	.2940***	.2310***
		(.0456)	(.0349)	(.0373)	(.0482)	(.0347)	(.0379)
β_e		.2912***	.2899***	.2540***	.2809***	.2827***	.2331***
		(.0274)	(.0255)	(.0269)	(.0264)	(.0256)	(.0282)
Intercept	19.4226***	9.0868***	9.0868***	11.2472***	9.7560***	13.0053***	12.2709***
	(.1317)	(2.3375)	(2.3375)	(2.4029)	(2.3273)	(2.2824)	(2.4639)
Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
R^2	.2631	.4251	.4251	.4096	.4292	.4292	.3806
$Adj.R^2$	.2628	.4172	.4172	.4015	.4206	.4206	.3713
$Num.obs.$	5209	5063	5063	5063	5063	5063	5063

*Notes: The dependent variable is the logarithm of the firm's output level. Fixed effects include both time and industry fixed effects. Standard errors are shown in parentheses. Significance levels are indicated as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The parameter λ measures the technology spillover effects, while ρ captures substitution effects. Subscripts on these parameters indicate interactions across different groups; for example, λ_{mn} quantifies the spillover from immigrant-led to native-led firms. β_p represents the productivity impact, measured by the logarithm of lagged R&D stock, and β_e quantifies the effect of effort level, also in logarithmic terms, represented by R&D expenditure.*

When examining the interactions between U.S. firms, a similar pattern emerges as detailed in Table 5. The benefits of cooperation are shown to outweigh the competitive losses, which is evident from the consistently positive and larger magnitude of λ compared to ρ. Additionally, including year and firm fixed effects is crucial for mitigating omitted-variable bias. A closer examination of the influence of immigrant-led on purely native-led firms, measured by λ_{nm}, reveals a significant stimulation of innovation by immigrant firms.

6.2 Link Formation Model

Table 6 reports the estimation results for the network formation model. We focus our discussion on the fully specified models in Column (4) for the Global sample and Column (8) for the US sample.

6.2.1 Reduced-Form Estimates

We begin by interpreting the raw logistic regression coefficients in terms of odds ratios, which describe the likelihood of link formation conditional on observed covariates. The presence of immigrant executives (IM) is a strong predictor of collaboration in both samples. In the Global sample, having an immigrant executive increases the odds of forming an R&D alliance by approximately 66% ($\exp(0.5082) \approx 1.66$). In the US sample, this effect is substantially larger, with the presence of immigrant executives roughly tripling the odds of collaboration relative to the baseline ($\exp(1.1120) \approx 3.04$).

Regarding social ties, the Global sample exhibits significant national homophily: sharing the same country of origin increases the odds of collaboration by 78% ($\exp(0.5776) \approx 1.78$). Conversely, the US sample displays a tendency toward heterophily; sharing a country of origin decreases the odds of collaboration by approximately 49% ($\exp(-0.6631) \approx 0.51$), suggesting that immigrant executives in the US are more likely to bridge structural holes between diverse groups rather than cluster within ethnic enclaves.

6.2.2 Identification of Structural Parameters

To move from likelihoods to economic preferences, we must account for the unobserved heterogeneity in each sample. The estimation results for the link formation models are presented in Table 6. From equation (15), we can recover the structural noise parameter ϑ by dividing the estimated coefficient of the interaction term $y_i y_j$ by the spillover effect λ obtained from the second-stage outcome equation. Since we do not assume heterogeneity in the dyadic characteristics regarding the cost deduction, we use the homogeneous spillover λ

given in column (4) of Table 4 and Table 5, which equals 0.0470 and 0.0551 for the Global and US samples, respectively.

Given that the logistic regression coefficients for $y_i y_j$ are 0.0076 (column (4)) and 0.0080 (column (8)) for the Global and US samples respectively, the estimated inverse noise parameter is $\hat{\vartheta} \approx 0.162$ for the Global sample and $\hat{\vartheta} \approx 0.145$ for the US sample. The parameter ϑ serves as the inverse temperature or sensitivity parameter in the network formation process, governing the trade-off between deterministic economic incentives and random idiosyncratic shocks (Hsieh et al., 2025b; Mele, 2017). A higher ϑ implies that firms' linking decisions are highly sensitive to the marginal profits defined by the model (high rationality), whereas as $\vartheta \to 0$, decisions become purely random. Our estimated values (0.145–0.162) are lower than those typically found in R&D network literature (e.g., ≈ 1.4 in Hsieh et al. (2025b)), suggesting that in our specific sample, the formation of collaborations is characterized by a significant degree of stochasticity or unobserved friction. While the synergy effect ($y_i y_j$) is statistically significant, the relatively low ϑ indicates that idiosyncratic factors (noise) play a substantial role in driving specific link formation decisions alongside the structural economic incentives.

6.2.3 Structural Interpretations

Accounting for the higher level of noise in the US sample ($\hat{\vartheta}_{US} < \hat{\vartheta}_{Global}$) reveals that the raw odds ratios understate the true magnitude of the structural preferences. We calculate the structural parameters as $\hat{\psi} = \hat{\beta}/\hat{\vartheta}$ to represent the underlying marginal utility of link formation.

Immigrant Effects and Homophily: The structural impact of immigrant executives is notably more pronounced than the reduced-form estimates suggest. In the Global sample, the presence of immigrant executives generates a structural utility gain of approximately 3.14 ($\approx 0.508/0.162$). In the US, correcting for the high market volatility reveals a massive structural premium of 7.67 ($\approx 1.112/0.145$). This implies that in the underlying payoff structure of US R&D networks, firms place a premium on the connectivity provided by immigrant executives that is more than double the global average.

Similarly, the structural divergence in homophily is stark. In the Global sample, sharing a country of origin yields a positive utility of 3.57, reducing the costs of coordination. In the US, the structural penalty for sharing an origin is -4.57, confirming that US-based immigrant executives actively seek diversity (heterophily). However, this does not imply a lack of social capital in the US; rather, the mechanism shifts from national origin to education. The structural utility of attending the same university ($SameUniversity$) in the US is 3.55, which effectively substitutes for the national-origin ties observed globally.

Network Structure and Other Controls: Finally, structural dependencies remain the dominant drivers of network formation across both samples. Relationship persistence (*PriorTie*) confers the largest utility advantage, with structural parameters of 9.77 (Global) and 8.20 (US), reflecting the high value of established trust. Triadic closure (*SharedPartner*) also provides a substantial and consistent utility gain of 7.61 (Global) and 7.32 (US), confirming that having common partners serves as a universal mechanism to mitigate information asymmetry.

Table 6: Regression Results of Network Formation Model

	Global Sample				US Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Immigrant	.9700***	.7546***	.5438***	.5082***	2.5276***	1.5260***	1.0849***	1.1120***
	(.0559)	(.0574)	(.0633)	(.0635)	(.3092)	(.3107)	(.3303)	(.3310)
SameOrigin	.6341***	.8060***	.6188***	.5776***	-.2986	-.6079	-.8619**	-.6631*
	(.0589)	(.0604)	(.0693)	(.0696)	(.3404)	(.3864)	(.3903)	(.3992)
$y_i y_j$		.0052***	.0077***	.0076***		.0057***	.0080***	.0080***
		(.0002)	(.0003)	(.0003)		(.0006)	(.0007)	(.0007)
SameCity			.6379***	.6547***			.3546	.3664
			(.1437)	(.1439)			(.4560)	(.4599)
SameIndustry			1.7946***	1.8000***			1.9582***	1.9403***
			(.0650)	(.0650)			(.1674)	(.1666)
PriorTie			1.5490***	1.5833***			1.2120***	1.1890***
			(.1269)	(.1276)			(.2812)	(.2856)
SharedPartner			1.0595***	1.2327***			.8455***	1.0613***
			(.0952)	(.0965)			(.2057)	(.2117)
DiffOutput			.0779***	.0805***			.0848***	.0956***
			(.0059)	(.0060)			(.0125)	(.0128)
DiffEffort			.0062	.0112*			-.0292	-.0385
			(.0055)	(.0059)			(.0254)	(.0277)
DiffProd			-.0097	-.0242***			.0873***	.0653**
			(.0060)	(.0065)			(.0259)	(.0284)
SameUniversity							.5884***	.5145***
							(.1633)	(.1639)
DiffEduB							.5937	.4865
							(.4601)	(.4538)
DiffEduG							-1.6532***	-1.6291***
							(.3979)	(.3940)
Female							.0219	.2123
							(.1549)	(.1584)
Intercept (γ_0)	-9.3958***	-11.1004***	-12.9928***	-11.9213***	-10.3568***	-10.9060***	-12.5510***	-11.3272***
	(.0395)	(.1128)	(.1674)	(.2188)	(.4547)	(.5177)	(.6077)	(.6668)
Time Effect (γ_t)	No	No	No	Yes	No	No	No	Yes
AIC	27463.8	23908.3	20678.5	20159.6	4291.6	3778.3	3149.9	3063.1
BIC	27506.2	23963.2	20828.8	20555.8	4327.6	3824.4	3321.6	3440.8
Log Likelihood	-13728.9	-11950.1	-10328.2	-10050.8	-2142.8	-1885.2	-1560.0	-1498.6
Deviance	27457.8	23900.3	20656.5	20101.6	4285.6	3770.3	3119.9	2997.1
Num. obs.	10190900	6880712	6339482	6339482	1207560	752532	691242	691242

*Notes: The dependent variable is a dummy indicating whether two firms establish an R&D collaboration or not. Significance levels are indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are shown in parentheses.*

7 Conclusion

This study bridges the gap between the economics of innovation, network science, and high-skilled migration. While previous literature has separately established that R&D collaborations enhance productivity and that immigrants contribute to patenting, we provide the first structural evidence of the mechanism binding these two forces: immigrant executives act as critical architects of the R&D networks that facilitate knowledge diffusion.

By employing a higher-order spatial autoregressive (SAR) model coupled with an endogenous network formation process, we overcome the identification challenges inherent in observational network data. Our structural estimation yields three novel insights regarding the dynamics of innovation.

First, we identify a massive "structural premium" associated with immigrant executives in the formation of R&D alliances. After correcting for unobserved market volatility, we find that the presence of immigrant executives reduces the friction of link formation by a factor of 3.14 globally and 7.67 in the United States. This indicates that in the US innovation ecosystem, immigrant executives are not merely participants but "super-connectors" who significantly lower the transaction costs of collaboration.

Second, our results uncover a fundamental divergence in social capital mechanisms between the global and US markets. Globally, R&D networks are driven by national homophily: firms connect with those of the same origin to minimize coordination costs. In contrast, the US market exhibits structural heterophily: immigrant-led firms in the US actively bridge structural holes by partnering with diverse firms, relying on university alumni networks rather than ethnic enclaves to establish trust. This suggests that the US assimilation model uniquely positions immigrant talent to facilitate cross-group knowledge transfer.

Third, regarding firm performance, we confirm that the network structure defined by these choices has significant economic consequences. We find robust evidence of positive R&D spillovers, where the connectivity facilitated by immigrant executives leads to tangible gains in firm output. Specifically, immigrant-led and foreign firms generate net positive externalities for native-led firms, dispelling the zero-sum view of high-skilled labor.

These findings carry profound policy implications. They suggest that immigration policy is, de facto, innovation policy. Restrictions on high-skilled immigration do not merely subtract individual workers from the labor force; they degrade the structural integrity of the R&D network itself, severing the links that drive aggregate productivity growth. Future research should extend this framework to examine the dynamic evolution of these networks over longer time horizons, particularly how shock-induced changes to immigration policy reconfigure the topology of global innovation.

8 Acknowledgment

The authors are grateful for the advice received from Andrei Barbos, Vincent Boucher, Bobby W. Chung, William Greene, and Michael D. König, as well as for the support from the Department of Economics. Appreciation is also given for the data collection efforts of Rezuanul Huq Rafi, Mohaimin Chowdhury, Safayet Hossain Tushar, Albab Amin Beky, Fatema Sobnam Moumita, Md Ifteker Chowdhury, MD. Borhan Uddin, Md. Nafiz Imtiaz, MD. Sadik Rahman, Rahul Barua, and Shahida Aktar.

References

Akcigit, Ufuk, Santiago Caicedo, Ernest Miguelez, Stefanie Stantcheva, and Valerio Sterzi (2018) "Dancing with the Stars: Innovation through Interactions,"Technical report, National Bureau of Economic Research.

Anderson, Simon P., Andre de Palma, and Jacques-Francois Thisse, *Discrete Choice Theory of Product Differentiation*.

Arkolakis, Costas, Sun Kyoung Lee, and Michael Peters (2020) "European immigrants and the United States' rise to the technological frontier," in *2019 Meeting Papers*, 1420.

Arp, Frithjof, Kate Hutchings, and Wendy A. Smith (2013) "Foreign executives in local organisations: An exploration of differences to other types of expatriates," *Journal of Global Mobility*, 1 (3), 312–335.

Bernstein, Shai, Rebecca Diamond, Abhisit Jiranaphawiboon, Timothy McQuade, and Beatriz Pousada (2022) "The contribution of high-skilled immigrants to innovation in the United States,"Technical report, National Bureau of Economic Research.

Bloom, Nicholas, Mark Schankerman, and John Van Reenen (2013) "Identifying technology spillovers and product market rivalry," *Econometrica*, 81 (4), 1347–1393.

Bolzani, Daniela and Alessandra Scandura (2024) "The role of collaboration networks for innovation in immigrant-owned new technology-based firms," *The Journal of Technology Transfer*, 49 (4), 1203–1233.

Brzozowski, Jan and Marco Cucculelli (2020) "Transnational Ties and Performance of Immigrant Firms: Evidence from Central Italy," *International Journal of Entrepreneurial Behavior & Research*, 26 (8), 1787–1806, 10.1108/IJEBR-10-2019-0582.

Flahaux, Marie-Laurence and Hein De Haas (2016) "African migration: trends, patterns, drivers," *Comparative migration studies*, 4, 1–25.

Ganguli, Ina and Megan MacGarvie (2025) "International Students, Immigration Policies and Implications for Innovation,"Technical report, National Bureau of Economic Research.

Glennon, Britta (2024) "Skilled Immigrants, Firms, and the Global Geography of Innovation," *Journal of Economic Perspectives*, 38 (1), 3–26.

Goyal, Sanjeev and José Luis Moraga-González (2001) "R&D Networks," *The RAND Journal of Economics*, 32 (4), 686–707, 10.2307/2696388.

Hambrick, Donald C. and Phyllis A. Mason (1984) "Upper Echelons: The Organization as a Reflection of Its Top Managers," *The Academy of Management Review*, 9 (2), 193–206, 10.2307/258434.

Hanaki, Nobuyuki, Ryo Nakajima, and Yoshiaki Ogura (2010) "The Dynamics of R&D Network in the IT Industry," *Research Policy*, 39 (3), 386–399, 10.1016/j.respol.2010.01.001.

Hsieh, Chih-Sheng, Michael D. König, and Xiaodong Liu (2025a) "Endogenous Technology Spillovers in R&D Collaboration Networks," *The RAND Journal of Economics*, 56 (4), 419–443, 10.1111/1756-2171.70010.

Hsieh, Chih-Sheng, Michael D König, and Xiaodong Liu (2025b) "Endogenous Technology Spillovers in R&D Collaboration Networks," *The RAND Journal of Economics*.

Hsieh, Chih-Sheng and Lung Fei Lee (2016) "A Social Interactions Model with Endogenous Friendship Formation and Selectivity," *Journal of Applied Econometrics*, 31 (2), 301–319, 10.1002/jae.2426.

Jackson, Matthew O. (2008) *Social and Economic Networks*: Princeton University Press.

Kale, Prashant, Harbir Singh, and Jeff Dyer (2004) "When to Ally and When to Acquire," *Harvard Business Review*.

Kerr, Sari Pekkala and William R Kerr (2019) "Immigrant networking and collaboration: Survey evidence from CIC,"Technical report, National Bureau of Economic Research.

Kim, Jerry W. and Monica C. Higgins (2007) "Where Do Alliances Come from?: The Effects of Upper Echelons on Alliance Formation," *Research Policy*, 36 (4), 499–514, 10.1016/j.respol.2007.02.017.

König, Michael D, Xiaodong Liu, and Yves Zenou (2019) "R&D networks: Theory, empirics, and policy implications," *Review of Economics and Statistics*, 101 (3), 476–491.

Krishnan, Rekha, Inge Geyskens, and Jan-Benedict E. M. Steenkamp (2016) "The Effectiveness of Contractual and Trust-Based Governance in Strategic Alliances under Behavioral and Environmental Uncertainty," *Strategic Management Journal*, 37 (12), 2521–2542, 10.1002/smj.2469.

Lee, Lung-Fei (2023) *Spatial econometrics: Spatial autoregressive models*, 1: World Scientific.

Levina, Natalia and Aimee A. Kane (2009) "Immigrant Managers as Boundary Spanners on Offshored Software Development Projects: Partners or Bosses?" in *Proceedings of the 2009 International Workshop on Intercultural Collaboration*, IWIC '09, 61–70, New York, NY, USA: Association for Computing Machinery, February, 10.1145/1499224.1499236.

Lin, Daomi, Wei Zheng, Jiangyong Lu, Xiaohui Liu, and Mike Wright (2019) "Forgotten or Not? Home Country Embeddedness and Returnee Entrepreneurship," *Journal of World Business*, 54 (1), 1–13, 10.1016/j.jwb.2018.08.003.

Mahroum, Sami (1999) "Competing for the highly skilled: Europe in perspective," *Science and Public Policy*, 26 (1), 17–25.

——— (2000) "Highly Skilled Globetrotters: Mapping the International Migration of Human Capital," *R&D Management*, 30 (1), 23–32, 10.1111/1467-9310.00154.

——— (2001) "Europe and the Immigration of Highly Skilled Labour," *International Migration*, 39 (5), 27–43, 10.1111/1468-2435.00170.

Mahroum, Sami and Rashid Ansari (2017) "What the data tells us about immigrant executives in the US," *Harvard Business Review Digital Article, November*, 29.

Manski, Charles F (1993) "Identification of endogenous social effects: The reflection problem," *The review of economic studies*, 60 (3), 531–542.

McFadden, Daniel (1972) "Conditional Logit Analysis of Qualitative Choice Behavior."

Mele, Angelo (2017) "A Structural Model of Dense Network Formation," *Econometrica*, 85 (3), 825–850, 10.3982/ECTA10400.

Platonova, Anna and Giuliana Urso (2013) "Asian immigration to the European Union, United States and Canada: an initial comparison," *Journal of Global Policy and Governance*, 1 (2), 143–156.

Prato, Marta (2022) "The global race for talent: Brain drain, knowledge transfer, and growth," *Knowledge Transfer, and Growth (November 27, 2022)*.

Rezaei, Shahamak (2011) "Trust as a Coopetititive Strategy in a Global Co-Ethnic Market: Towards an Empirically Supported Theory," *International Journal of Business and Globalisation*, 7 (3), 265, 10.1504/IJBG.2011.042059.

Schilling, Melissa A (2009) "Understanding the alliance data," *Strategic Management Journal*, 30 (3), 233–260.

Tomasello, Mario Vincenzo, Mauro Napoletano, Antonios Garas, and Frank Schweitzer (2016) "The Rise and Fall of R&D Networks," *Industrial and Corporate Change*, dtw041, 10.1093/icc/dtw041.

Useche, Diego, Ernest Miguelez, and Francesco Lissoni (2020) "Highly Skilled and Well Connected: Migrant Inventors in Cross-Border M&As," *Journal of International Business Studies*, 51 (5), 737–763.

Wadhwa, Vivek, AnnaLee Saxenian, Ben Rissing, and Gary Gereffi (2007) "America's new immigrant entrepreneurs," *Kauffman Foundation report*.

Zacchia, Paolo (2020) "Knowledge Spillovers through Networks of Scientists," *The Review of economic studies*, 87 (4), 1989–2018.

9 Appendix

9.1 Tables

Table 7: Firms Count by Region

Name	Code	Count	Rank	Name	Code	Count	Rank
United States	US	348	1	Norway	NO	5	20
Japan	JP	136	2	Finland	FI	4	21
China	CN	92	3	Spain	ES	4	22
Canada	CA	57	4	Brazil	BR	2	23
United Kingdom	GB	46	5	Italy	IT	2	24
South Korea	KR	43	6	Thailand	TH	2	25
Australia	AU	41	7	Austria	AT	1	26
France	FR	32	8	Hungary	HU	1	27
Germany	DE	31	9	Indonesia	ID	1	28
Taiwan	TW	26	10	Luxembourg	LU	1	29
India	IN	24	11	Malaysia	MY	1	30
Sweden	SE	20	12	New Zealand	NZ	1	31
Switzerland	CH	17	13	Philippines	PH	1	32
Israel	IL	16	14	Poland	PL	1	33
Netherlands	NL	15	15	Russia	RU	1	34
Denmark	DK	11	16	Singapore	SG	1	35
Ireland	IE	10	17	Virgin Islands, British	VG	1	36
Hong Kong	HK	8	18	South Africa	ZA	1	37
Belgium	BE	7	19				

Table 8: Origins of All Senior Executives in US Firms

Origin	Count	Proportion (%)	Rank	Origin	Count	Proportion (%)	Rank
US	46,205	81.26	1	CO	20	0.035	44
GB	2,066	3.634	2	FI	20	0.035	44
IN	1,481	2.605	3	PH	18	0.032	45
CA	815	1.433	4	RO	18	0.032	45
FR	746	1.312	5	Sl	17	0.030	46
DE	575	1.011	6	PR	14	0.025	47
IT	380	0.668	7	TG	14	0.025	47
CN	370	0.651	8	HU	13	0.023	48
AU	349	0.614	9	PS	13	0.023	48
IL	303	0.533	10	SY	13	0.023	48
ES	210	0.369	11	MF	12	0.021	49
ZA	210	0.369	11	ET	11	0.019	50
BR	205	0.361	12	BD	10	0.018	51
MX	181	0.318	13	DO	10	0.018	51
IE	180	0.317	14	MA	10	0.018	51
NL	176	0.310	15	TZ	10	0.018	51
JP	170	0.299	16	ZW	10	0.018	51
IR	158	0.278	17	MY	9	0.016	52
BE	133	0.234	18	BG	8	0.014	53
RU	129	0.227	19	IS	8	0.014	53
SE	122	0.215	20	LR	8	0.014	53
CH	105	0.185	21	NP	8	0.014	53
KR	103	0.181	22	SK	8	0.014	53
AR	102	0.179	23	CY	7	0.012	54
TR	100	0.176	24	AM	6	0.011	55
PL	88	0.155	25	CR	6	0.011	55
TW	78	0.137	26	MT	5	0.009	56
LB	75	0.132	27	PA	4	0.007	57
KP	74	0.130	28	UM	4	0.007	57
GR	58	0.102	29	CM	3	0.005	58
EG	54	0.095	30	SI	3	0.005	58
DK	51	0.090	31	SL	3	0.005	58
AT	49	0.086	32	UK	3	0.005	58
NZ	45	0.079	33	BY	2	0.004	59
SG	44	0.077	34	LK	2	0.004	59
CU	40	0.070	35	MK	2	0.004	59
HK	38	0.067	36	SA	2	0.004	59
PK	35	0.062	37	ST	2	0.004	59
CL	30	0.053	38	UY	2	0.004	59
VN	30	0.053	38	AL	1	0.002	60
SZ	29	0.051	39	HR	1	0.002	60
VE	28	0.049	40	JM	1	0.002	60
PT	24	0.042	41	LT	1	0.002	60
NG	23	0.040	42	RS	1	0.002	60
NO	23	0.040	42	TH	1	0.002	60
UA	22	0.039	43	**Total: 56,856**			

Note: The abbreviated name for each origin follows the ISO 3166-1 alpha-2 code standard. For further information, please visit https://www.isin.net/country-codes/.

Table 9: Sample Company Profile

Year	Symbol	Company Name	Country	State	City	Latitude[1]	Longitude[1]	SIC[2] Code	SIC[2] Group
2003	PFE	Pfizer Inc.	US	NY	New York	40.7127281	-74.0060152	2834	Drug Manufacturers—General
2004	PFE	Pfizer Inc.	US	NY	New York	40.7127281	-74.0060152	2834	Drug Manufacturers—General
2005	PFE	Pfizer Inc.	US	NY	New York	40.7127281	-74.0060152	2834	Drug Manufacturers—General
2006	PFE	Pfizer Inc.	US	NY	New York	40.7127281	-74.0060152	2834	Drug Manufacturers—General
2007	PFE	Pfizer Inc.	US	NY	New York	40.7127281	-74.0060152	2834	Drug Manufacturers—General
2008	PFE	Pfizer Inc.	US	NY	New York	40.7127281	-74.0060152	2834	Drug Manufacturers—General
2009	PFE	Pfizer Inc.	US	NY	New York	40.7127281	-74.0060152	2834	Drug Manufacturers—General
2010	PFE	Pfizer Inc.	US	NY	New York	40.7127281	-74.0060152	2834	Drug Manufacturers—General
2011	PFE	Pfizer Inc.	US	NY	New York	40.7127281	-74.0060152	2834	Drug Manufacturers—General
2012	PFE	Pfizer Inc.	US	NY	New York	40.7127281	-74.0060152	2834	Drug Manufacturers—General
2013	PFE	Pfizer Inc.	US	NY	New York	40.7127281	-74.0060152	2834	Drug Manufacturers—General
2014	PFE	Pfizer Inc.	US	NY	New York	40.7127281	-74.0060152	2834	Drug Manufacturers—General
2015	PFE	Pfizer Inc.	US	NY	New York	40.7127281	-74.0060152	2834	Drug Manufacturers—General
2016	PFE	Pfizer Inc.	US	NY	New York	40.7127281	-74.0060152	2834	Drug Manufacturers—General
2017	PFE	Pfizer Inc.	US	NY	New York	40.7127281	-74.0060152	2834	Drug Manufacturers—General
2018	PFE	Pfizer Inc.	US	NY	New York	40.7127281	-74.0060152	2834	Drug Manufacturers—General
2019	PFE	Pfizer Inc.	US	NY	New York	40.7127281	-74.0060152	2834	Drug Manufacturers—General
2020	PFE	Pfizer Inc.	US	NY	New York	40.7127281	-74.0060152	2834	Drug Manufacturers—General
2021	PFE	Pfizer Inc.	US	NY	New York	40.7127281	-74.0060152	2834	Drug Manufacturers—General
2022	PFE	Pfizer Inc.	US	NY	New York	40.7127281	-74.0060152	2834	Drug Manufacturers—General

[1] The latitude and longitude coordinates have been retrieved via the Google Maps API.

[2] The Standard Industrial Classification (SIC) is a system used to classify industries by a four-digit code. This system was originally developed in the United States in the 1930s to facilitate the collection, presentation, and analysis of statistical data related to businesses and industries. The classification is based on the primary type of economic activity a company engages in.

Table 10: Sample Company Profile Continue 1

Year	Symbol[1]	CoB[2]	N_F[3]	Edu_N[4]	Edu_B[5]	Edu_M[6]	Edu_D[7]	University[8]	N_ex[9]
2003	PFE	US	0	0	1	0	1	Georgetown University School of Medicine; Tufts University; Harvard University	2
2004	PFE	CA;US	0	0	0	0	2	University of British Columbia; Stanford Business School; Tufts University; Harvard University	2
2005	PFE	CA;US	0	0	0	0	2	University of British Columbia; Stanford Business School; Tufts University; Harvard University	2
2006	PFE	US;GB	0	0	1	3	2	New York University Stern School of Business; Stern School of Business; Oakland/Michigan State University; St. John's University; St. Peter's College; Imperial College London; Boston College; University of New Hampshire; Princeton University; Heriot-Watt University; University of Edinburgh	6
2007	PFE	US;GB	0	0	1	3	2	New York University Stern School of Business; Stern School of Business; Oakland/Michigan State University; St. John's University; St. Peter's College; Imperial College London; Boston College; University of New Hampshire; Princeton University; Heriot-Watt University; University of Edinburgh	6
2008	PFE	US	0	0	0	0	1	Stanford University; University of California, Berkeley	1
2009	PFE	US;GB	1	0	2	1	0	St. John's University; St. Peter's College; Johns Hopkins University; Howard University Medical School; Imperial College London	3
2010	PFE	US;GB;SE	0	0	2	1	1	St. John's University; St. Peter's College; Albany College of Pharmacy and Health Sciences; Imperial College London; University of Lund	4

Table 11: Sample Company Profile Continue 2

Year	Symbol[1]	CoB[2]	N_F[3]	Edu_N[4]	Edu_B[5]	Edu_M[6]	Edu_D[7]	University[8]	N_ex[9]
2011	PFE	US;GB;SE	1	0	3	1	2	Wesleyan University; Yale Law School; Carnegie Mellon University; St. John's University; St. Peter's College; Albany College of Pharmacy and Health Sciences; Imperial College London; University of Lund	6
2012	PFE	US;GB;SE	1	0	2	1	2	Wesleyan University; Yale Law School; St. John's University; St. Peter's College; Albany College of Pharmacy and Health Sciences; Imperial College London; University of Lund	5
2013	PFE	US;GB;SE;FR	1	0	2	3	2	Wesleyan University; Yale Law School; St. John's University; St. Peter's College; Albany College of Pharmacy and Health Sciences; Imperial College London; Glasgow University; Strathclyde Graduate Business School; University of Lund; Paris Descartes University; University of Paris XII	7
2014	PFE	US;GB;SE	0	0	2	2	1	St. John's University; St. Peter's College; Albany College of Pharmacy and Health Sciences; Imperial College London; Glasgow University; Strathclyde Graduate Business School; University of Lund	5
2015	PFE	US;GB;SE	0	0	2	2	1	St. John's University; St. Peter's College; Albany College of Pharmacy and Health Sciences; Imperial College London; Glasgow University; Strathclyde Graduate Business School; University of Lund	5
2016	PFE	GR;US;GB;SE	0	0	2	2	2	Aristotle University of Thessaloniki; St. John's University; St. Peter's College; Albany College of Pharmacy and Health Sciences; Imperial College London; Glasgow University; Strathclyde Graduate Business School; University of Lund	6
2017	PFE	GR;US;GB;SE	0	0	1	2	2	Aristotle University of Thessaloniki; St. John's University; St. Peter's College; Imperial College London; Glasgow University; Strathclyde Graduate Business School; University of Lund	5

Table 12: Sample Company Profile Continue 3

Year	Symbol[1]	CoB[2]	N_F[3]	Edu_N[4]	Edu_B[5]	Edu_M[6]	Edu_D[7]	University[8]	N_ex[9]
2018	PFE	GR;US;GB;SE	0	0	1	2	2	Aristotle University of Thessaloniki; St. John's University; St. Peter's College; Imperial College London; Glasgow University; Strathclyde Graduate Business School; University of Lund	5
2019	PFE	GR;US;GB;SE	0	0	1	2	2	Aristotle University of Thessaloniki; St. John's University; St. Peter's College; Imperial College London; Glasgow University; Strathclyde Graduate Business School; University of Lund	5
2020	PFE	ZA;US;GB;SE	1	0	0	3	1	University of Cape Town; Cornell University; St. John's University; St. Peter's College; Glasgow University; Strathclyde Graduate Business School; University of Lund	4
2021	PFE	ZA;US;GB;SE	1	0	1	3	1	University of Cape Town; Cornell University; Cornell Law School; St. John's University; St. Peter's College; Glasgow University; Strathclyde Graduate Business School; University of Lund	5
2022	PFE	ZA;US;SE	2	0	0	3	2	University of Cape Town; Cornell University; Kansas State University; Babcock Graduate School of Management at Wake Forest University; St. John's University; St. Peter's College; University of Lund; Harvard University; Yale University	5

[1] A ticker symbol uniquely identifies a publicly traded company.
[2] Countries of birth for the senior executives.
[3] Total count of female executives.
[4] Number of executives without any college-level degree.
[5] Number of executives whose highest degree is bachelor.
[6] Number of executives whose highest degree is master, including MBA.
[7] Number of executives holding doctoral degree, including MD, JD, and PhD.
[8] Universities attended by the executives.
[9] Overall number of executives.

9.2 Endogeneity of the Spatial Lag[3]

In the SAR model, the spatial lag $\mathbf{Wy}$ (where $\mathbf{W}$ is the spatial weight matrix and $\mathbf{y}$ is the outcome vector) introduces endogeneity because $\mathbf{Wy}$ is influenced by $\mathbf{y}$, which is also an endogenous component of the model. This *reciprocal causation* makes $\mathbf{Wy}$ correlated with the error term $\mathbf{V}$, violating the classical assumptions required for ordinary least squares (OLS) regression.

The SAR model is expressed as:

$$\mathbf{y} = \rho\mathbf{Wy} + \mathbf{X}\beta + \mathbf{V}, \quad \text{where } \mathbf{V} \sim \mathcal{N}(0, \sigma^2\mathbf{I}) \tag{A1}$$

In this framework, $\mathbf{Wy}$ is referred to as the spatial lag, ρ is the spatial autoregressive parameter, which is often interpreted as representing spillover effects. The multiplier effect can be quantified as $\frac{1}{1-\rho}$ Lee (2023). The matrix $\mathbf{X} = (\mathbf{x}_1^\top, \ldots, \mathbf{x}_n^\top)$ represents an $n \times k$ matrix of observations on k exogenous variables, β is a k-dimensional vector of coefficients, and $\mathbf{V} = (\epsilon_1, \ldots, \epsilon_n)^\top$ where ϵ_i conditional on $\mathbf{A}, \mathbf{X}$ follows a normal distribution $N(0, \sigma^2)$.

Suppose $\mathbf{I}_n - \rho\mathbf{W}$ is nonsingular (i.e., invertible), then

$$\mathbf{y} = (\mathbf{I}_n - \rho\mathbf{W})^{-1}\mathbf{X}\beta + (\mathbf{I}_n - \rho\mathbf{W})^{-1}\boldsymbol{\epsilon}. \tag{A2}$$

Note that $\mathbf{I}_n - \rho\mathbf{W}$ is nonsingular if $|\rho| < 1/\|\mathbf{W}\|$, where $\|\cdot\|$ is any matrix norm (e.g., the largest eigenvalue/Perron-Frobenius eigenvalue).

From the reduced form of Eq. (A1), we get

$$\mathbf{Wy} = \mathbf{W}(\mathbf{I}_n - \rho\mathbf{W})^{-1}\mathbf{X}\beta + \mathbf{W}(\mathbf{I}_n - \rho\mathbf{W})^{-1}\boldsymbol{\epsilon}. \tag{A3}$$

Since

$$\mathbb{E}[\boldsymbol{\epsilon}^\top\mathbf{Wy}] = \mathbb{E}[\boldsymbol{\epsilon}^\top\mathbf{W}(\mathbf{I}_n - \rho\mathbf{W})^{-1}\mathbf{X}\beta] + \mathbb{E}[\boldsymbol{\epsilon}^\top\mathbf{W}(\mathbf{I}_n - \rho\mathbf{W})^{-1}\boldsymbol{\epsilon}],$$

we have

$$\mathbb{E}[\boldsymbol{\epsilon}^\top\mathbf{W}(\mathbf{I}_n - \rho\mathbf{W})^{-1}\mathbf{X}\beta] = 0,$$

and

$$\mathbb{E}[\boldsymbol{\epsilon}^\top\mathbf{W}(\mathbf{I}_n - \rho\mathbf{W})^{-1}\boldsymbol{\epsilon}] = \sigma^2\,\mathrm{tr}[\mathbf{W}(\mathbf{I}_n - \rho\mathbf{W})^{-1}] \neq 0.$$

Hence, the spatial lag $\mathbf{Wy}$ is **endogenous**.

[3]This Appendix is based on lecture materials from Prof. Michael D. König, Department of Spatial Economics at VU Amsterdam.

9.2.1 Why IV can be a solution

From Eq. (A2) we find that

$$\mathbb{E}[\mathbf{W}\mathbf{y}] = \mathbf{W}(\mathbf{I}_n - \rho\mathbf{W})^{-1}\mathbf{X}\boldsymbol{\beta}.$$

Applying Carl Neumann's result on matrices we know $|\rho| < 1/\|\mathbf{W}\|$, then

$$(\mathbf{I}_n - \rho\mathbf{W})^{-1} = \mathbf{I}_n + \rho\mathbf{W} + \rho^2\mathbf{W}^2 + \dots.$$

Therefore,

$$\mathbb{E}[\mathbf{W}\mathbf{y}] = \mathbf{W}\mathbf{X}\beta + \rho\mathbf{W}^2\mathbf{X}\beta + \rho^2\mathbf{W}^3\mathbf{X}\beta + \dots,$$

which can be rewritten as

$$\mathbb{E}[\mathbf{W}\mathbf{y}] = [\mathbf{W}\mathbf{X}, \mathbf{W}^2\mathbf{X}, \mathbf{W}^3\mathbf{X}, \dots] \begin{bmatrix} \beta \\ \rho\beta \\ \rho^2\beta \\ \vdots \end{bmatrix}.$$

Thus, the terms $[\mathbf{W}\mathbf{X}, \mathbf{W}^2\mathbf{X}, \mathbf{W}^3\mathbf{X}, \dots]$ can be used as instrumental variables (IVs) for $\mathbf{W}\mathbf{y}$.

Let $\mathbf{Z} = [\mathbf{X}, \mathbf{W}\mathbf{X}, \mathbf{W}^2\mathbf{X}, \dots, \mathbf{W}^p\mathbf{X}]$ be the $n \times h$ IV matrix. Then

$$\mathbb{E}[\mathbf{Z}^\top\boldsymbol{\epsilon}] = 0.$$

9.2.2 Why MLE can be a solution

MLE solves the endogeneity issue in SAR models by explicitly incorporating the dependence between $\mathbf{Y}$ and $\mathbf{W}\mathbf{Y}$ in the likelihood function. It models the spatial dependence structurally and makes correlation among observations accounted for in the estimation process.

Suppose $\boldsymbol{\epsilon}|\mathbf{W}, \mathbf{X} \sim \mathcal{N}(0, \sigma^2\mathbf{I}_n)$. Then from Eq. (A2), we have:

$$\mathbf{y} \sim \mathcal{N}(\mu_y, \Sigma_y),$$

where

$$\mu_y = (\mathbf{I}_n - \rho\mathbf{W})^{-1}\mathbf{X}\beta,$$
$$\Sigma_y = \sigma^2(\mathbf{I}_n - \rho\mathbf{W})^{-1}(\mathbf{I}_n - \rho\mathbf{W}^\top)^{-1}.$$

The joint density of $\mathbf{y}$ is then:

$$f(\mathbf{y}) = (2\pi)^{-\frac{n}{2}}(\det\Sigma_y)^{-\frac{1}{2}}\exp\left\{-\frac{1}{2}(\mathbf{y}-\mu_y)^\top\Sigma_y^{-1}(\mathbf{y}-\mu_y)\right\}.$$

The log-likelihood is given by:

$$\mathcal{L}(\rho,\beta,\sigma^2) = -\frac{n}{2}\ln(2\pi) - \frac{n}{2}\ln\sigma^2 + \ln|\mathbf{I}_n - \rho\mathbf{W}| - \frac{1}{2\sigma^2}\epsilon(\delta)^\top\epsilon(\delta), \tag{A4}$$

where

$$\epsilon(\delta) = \mathbf{y} - \mathbf{Z}\delta = \mathbf{y} - \rho\mathbf{W}\mathbf{y} - \mathbf{X}\beta.$$

The first-order conditions (FOCs) are given by:

$$\frac{\partial\mathcal{L}}{\partial\rho} = -\mathrm{tr}\left[\mathbf{W}(\mathbf{I}_n - \rho\mathbf{W})^{-1}\right] + \frac{1}{\sigma^2}(\mathbf{W}\mathbf{y})^\top\epsilon(\delta) = 0, \tag{A5}$$
$$\frac{\partial\mathcal{L}}{\partial\beta} = \frac{1}{\sigma^2}\mathbf{X}^\top\epsilon(\delta) = 0, \tag{A6}$$
$$\frac{\partial\mathcal{L}}{\partial\sigma^2} = -\frac{n}{2\sigma^2} + \frac{1}{2\sigma^4}\epsilon(\delta)^\top\epsilon(\delta) = 0. \tag{A7}$$

From Eq. (A6), we get:

$$\beta = (\mathbf{X}^\top\mathbf{X})^{-1}\mathbf{X}^\top(\mathbf{I}_n - \rho\mathbf{W})\mathbf{y}.$$

Substituting β into Eq. (A7) gives:

$$\sigma^2 = \frac{1}{n}\mathbf{y}^\top(\mathbf{I}_n - \rho\mathbf{W})^\top\mathbf{M}_\mathbf{X}(\mathbf{I}_n - \rho\mathbf{W})\mathbf{y},$$

where $\mathbf{M}_\mathbf{X} = \mathbf{I}_n - \mathbf{X}(\mathbf{X}^\top\mathbf{X})^{-1}\mathbf{X}^\top$.

Substituting β and σ^2 into Eq. (A4) gives:

$$\mathcal{L}(\rho) = -\frac{n}{2}(1 + \ln(2\pi)) - \frac{n}{2}\ln\sigma^2(\rho) + \ln|\mathbf{I}_n - \rho\mathbf{W}|,$$

where

$$\sigma^2(\rho) = \frac{1}{n}\mathbf{y}^\top(\mathbf{I}_n - \rho\mathbf{W})^\top\mathbf{M}_\mathbf{X}(\mathbf{I}_n - \rho\mathbf{W})\mathbf{y}.$$

Finally, the MLEs are given by:

$$\hat{\rho}_{\mathrm{MLE}} = \arg\max_{\rho} \mathcal{L}(\rho), \tag{A8}$$

$$\hat{\beta}_{\mathrm{MLE}} = (\mathbf{X}^\top \mathbf{X})^{-1} \mathbf{X}^\top (\mathbf{I}_n - \hat{\rho}_{\mathrm{MLE}} \mathbf{W}) \mathbf{y}, \tag{A9}$$

$$\hat{\sigma}^2_{\mathrm{MLE}} = \frac{1}{n} \mathbf{y}^\top (\mathbf{I}_n - \hat{\rho}_{\mathrm{MLE}} \mathbf{W})^\top \mathbf{M}_{\mathbf{X}} (\mathbf{I}_n - \hat{\rho}_{\mathrm{MLE}} \mathbf{W}) \mathbf{y}. \tag{A10}$$