The bureaucratic politics of networks: How patronage shapes intergovernmental collaboration*

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Abstract

How does patronage—the political appointment of bureaucrats—affect coordination and joint delivery among public organisations? Research has examined patronage's effects on bureaucratic performance, but mostly within hierarchical, top-down policymaking. Yet growing fragmentation and complexity in domains such as environmental governance make policy dependent on horizontal networks of intergovernmental collaboration. This paper develops a theoretical framework and new evidence linking patronage to the incentives and capacities that shape such collaboration. Patronage can deter coordination by reducing bureaucratic capacity but may also promote it by leveraging appointees' political capital. To test these claims, I analyse environmental collaboration agreements among the universe of Colombian public agencies using Exponential Random Graph Models (ERGMs). To account for the nested structure of the data, I develop an extension of ERGMs that incorporate regional random effects. Results show that patronage has heterogeneous effects: managerial patronage fosters collaboration, while professional-level patronage inhibits it. I further show that these effects are conditioned by organisations' specialised knowledge, stability and experience. The findings underscore patronage's contingent role in governance networks and the importance of bureaucratic politics in collaborative policy delivery.

Keywords: Patronage, Intergovernmental Collaborations, Policy Networks, Environmental Governance, Colombia

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1. Introduction

How do political appointments affect public bureaucracies' coordination and joint delivery of policies? To date, research on the effects of patronage appointments on the government's performance and outcomes has focused almost exclusively on the hierarchical, principal-agent dynamics of public organisations as isolated, top-down policymaking and implementation actors (Brierley et al., 2022; Dahlström & Lapuente, 2022). In contrast, scholars and practitioners have long been promoting and experimenting with forms of governance that rely on the cooperation between government entities to coordinate and collaboratively deliver national and subnational policies (Ansell & Gash, 2008; Lubell et al., 2010; Ostrom, 1990). These forms of collaborative governance have been argued to be necessary to deal with increasing political and administrative fragmentation and—particularly in cases such as natural resources management—overcome the collective action challenges imposed by common-pool resources (Bodin, 2017; Ostrom, 2010). However, little is known about how patronage—the assignment of public jobs on political grounds (Panizza et al., 2019)—shapes the capacity and willingness of public organisations to engage in such forms of joint policy delivery.

Theories of political patronage typically draw on the principal-agent framework to propose that political appointments minimise the challenges of coordination between political principals and their bureaucratic agents, and focus on the positive or negative effects of those solutions on government outputs—e.g., easing engagement in maleficence thus distorting services provision (Brierley, 2020; Bussell, 2019) or enhancing accountability and monitoring mechanisms to improve delivery (Jiang, 2018; Toral, 2023). However, patronage research has largely ignored its impact on coordination between policy actors that *do not necessarily have a clear relationship of political subordination*. Voluntary interorganisational arrangements—besides the challenges of traditional bureaucratic policymaking—entail collective action dilemmas that require, among others, aligning diverse organisational interests, negotiating resource dependencies, costs and benefits distribution, and establishing governance structures that facilitate joint problem-solving and implementation (Ostrom, 1990; Provan & Milward, 1995; 2001; Agranoff & McGuire, 2001; Kim et al., 2022; Lubell, 2013). How patronage affects the behaviours and institutions enabling cooperation among public organisations remains unaddressed.

This is a problematic omission because governance systems around the world, both North and South, are increasingly defined by the decentralised interactions between different autonomous but interdependent public organisations, creating a complex horizontal and fragmented distribution of power that has reduced the relative incidence of the unitary action of the central state (Faguet, 2012; Bodin, 2017; Cole, 2011; Jordan et al., 2018). The quality of governance under these settings hinges on the ability of national and subnational bureaucracies to overcome the potential turf conflicts and collective action dilemmas created by the fragmentation and overlapping of authority (Faguet, 2014). However, interagency coordination and collaboration is highly dependent on the political incentives associated with the expected benefits, the transaction costs, and the risks of joint action (Lubell et al., 2002; Gerber & Gibson, 2009; Gerber et al., 2013). Therefore, the extent to which a political incumbent shapes the preferences and capacities of a public bureaucracy should arguably impact the chances that such forms of collaborative delivery occur.

Here, I build on patronage, and collaborative and network governance literatures to propose a theoretical framework that links the logics of patronage to the emergence of interorganisational collaboration. I propose that patronage disrupts two bureaucratic resources that are crucial for the establishment of collaboration: organisational stability and technical policy knowledge. By increasing bureaucratic turnover (Toral, 2024) and replacing technical competence with political loyalty (Lewis, 2011), higher levels of patronage increase the risks of defection, and reduce the policy domain knowledge required to initiating and sustaining collaborations. Contrastingly, I also propose that patronage appointees can be instrumental in facilitating collaborations. If appointees are endowed with political capital, they can leverage their networks, previous knowledge of the system, and access to informal structural power to facilitate the establishment of agreements, negotiate bargains, and mobilise common policy interests, thus increasing the chances of agencies participating in joint ventures. Importantly, the argument is not that patronage necessarily produces a virtuous collaborative governance. What I posit is that patronage appointments can also increase the chances of a public organisation engaging in joint ventures with other public stakeholders.

I test my theoretical arguments by analysing all the environmental collaborative projects among public agencies in Colombia between 2017 and 2024. Colombia has an emergent tradition of decentralised environmental and natural resources management and offers high subnational variation in terms of the influence of local and national politicians over bureaucratic selection. This setting offers a most likely case for testing the hypotheses advanced here. Using text analysis methods, I identified and classified all public collaborative agreements (N = 4,791) signed between organisations from all levels of government—including municipalities, local development agencies, regional governments, subregional environmental authorities, national level ministries, among others—and matched it to fine-grained employer-employee public records containing information on the universe of civil servants in the country (N = 203,817). Because collaboration between agencies might feature second-order (e.g., common characteristics between partners such as political homophily) and third-order dependencies (e.g., collaboration is more likely to occur if organisations have a partner in common), I use hierarchical mixed Exponential Random Graph Models (mERGMs) to model the emergence of ties between public organisations. Building on the iterative estimation procedure proposed by Kevork and Kauermann (2022), I propose this hierarchical extension to the ERGM framework to account for the regional heterogeneities and the hierarchical embeddedness of collaboration dynamics in the national network. The findings demonstrate that, at the aggregate level, patronage does not have a clear effect on the probabilities of forming collaborations. However, when patronage is disaggregated by hierarchical level of the appointments, the analyses show important nuances: managerial patronage increases the likelihood of collaborative ties while patronage at lower ranks decreases it. Using moderation analyses, I show that the potentially beneficial effects of patronage are mainly realised once there is a stable bureaucratic base to leverage appointees' capital and primarily among co-partisan partners.

The contribution of this paper is three-fold. Firstly, it (re)connects network and collaborative governance literature with the debates of the politics of bureaucracy scholarship. The focus of governance literature on non-state actors has implied a poor conceptualisation and consideration of the roles and dynamics of bureaucratic actors and their impact on horizontal modes of governance (Biesbroek, Lesnikowski, et al., 2018; Biesbroek, Peters, et al., 2018). Here, I show how a "traditional" bureaucratic issue, such as the politicisation of public employment, is an important factor that can shape the formation and structure of voluntary joint action. Ignoring the role of the politics of the bureaucracy can lead to misinterpreting the potential failures or successes of these modes of policy delivery. Secondly, I extend the recent advances of the patronage literature to a novel field where its effects have not been yet studied—i.e., collaborative and network governance. Complementing the findings that patronage can have both positive and negative impacts on governance processes and outcomes (Brierley, 2021; Brierley et al., 2022; Dahlström & Lapuente, 2022), this paper shows that patronage appointments impact heterogeneously horizontal and decentralised modes of policy delivery. Finally, complementing the literature on the political economy of environmental governance (Dijkstra & Fredriksson, 2010; Fredriksson & Wollscheid, 2014; Hu et al., 2021), I theorise and show the relevance of the interplay between the political and organisational dimensions of the bureaucracy for environmental governance processes.

2. Theoretical framework: Patronage appointments in governance networks

The concept of patronage is widely contested, and the literature provides many different—sometimes contrasting wider or narrower definitions (Kopecký et al., 2016; Panizza et al., 2018, 2019). Following Panizza et al. (2019, p.148), I define *patronage* as "the power of political actors to appoint individuals by discretion to non-elective positions in the public sector". Patronage has usually been defined in opposition to bureaucratic autonomy and public sector professionalisation (Dahlström et al., 2012; Fukuyama, 2013; Oliveros & Schuster, 2017; Peters, 2010). Comparative bureaucratic politics scholarship has shown that, by selecting loyal over competent personnel, political patrons may gain increased sway over bureaucratic decision-making, facilitating ideological policy alignment (Gallo & Lewis, 2011; Hollibaugh et al., 2014) and, potentially, incumbent's illicit use of public resources (Grindle, 2012; Brierley, 2020; Bussell, 2019). Political capture of public employment has thus been associated with lower government performance (Colonnelli et al., 2020; Lewis, 2007; Rauch & Evans, 2000) and increased public sector corruption (Dahlström et al., 2012; Meyer-Sahling et al., 2018; Oliveros & Schuster, 2017). More recently, scholars have also advanced theory and evidence to argue that the reduced distance between patrons and their appointees can lead to enhanced government outcomes—if politicians have the right incentives to demand increased output from their bureaucratic clients (Jiang, 2018; Toral, 2023).

How, then, can patronage shape the emergence of collaborative governance networks? I argue that political appointees may provide a crucial resource for intergovernmental collaboration: by leveraging their political and relational capital, well-connected appointees can increase the likelihood that bureaucracies engage in joint initiatives. Yet this potential benefit is contingent on two bureaucratic attributes that are often undermined by patronage. First, bureaucratic stability is weakened when political appointments heighten organisational turnover, disrupting the continuity required for sustained cooperation (Toral, 2021; Doherty, Lewis & Limbocker, 2019). Second, the specialised policy knowledge necessary for collaboration is eroded by the well-documented loyalty–competence trade-off, whereby incumbents prioritise political loyalty over technical expertise in their selection of bureaucrats (Lewis, 2007; Colonnelli, Prem & Teso, 2020). Thus, while patronage can enhance collaboration by mobilising political capital, it can simultaneously constrain it by diminishing the bureaucratic foundations upon which effective cooperation depends.

2.1. Political appointees as network facilitators

Not all patronage appointments are the same (Panizza et al., 2019). While patronage is often portrayed as a uniform practice of rewarding loyalty at the expense of bureaucratic quality, recent scholarship stresses its heterogeneity. Politicians may use appointments not only to reward electoral clients but also to strategically place trusted allies or skilled operatives in positions that advance their policy and coalition goals (Panizza et al., 2018; Kopecký et al., 2016). Typologies of patronage distinguish between clientelistic appointments, which primarily serve distributive or partisan purposes, and more strategic forms, in which appointees are selected for their capacity to deliver on organisational, political, or policy priorities. Indeed, although patronage allows incumbents to hire loyal servants and electoral clients at expenses of bureaucratic quality (Oliveros, 2021; Toral, 2023), politicians also have interests that might foster hiring strategic individuals in key positions (Brierley, 2021).

Furthermore, because of their political nature, many patronage appointments tend to have higher political capital and institutional, system-level knowledge. Their position and career depend on being well-connected. These are essential assets in governance networks because they enable a better ability to create links with other relevant stakeholders. Patronage studies usually concentrate on the perspective of the political patron. However, appointed clients are also strategic political actors. Understanding their incentives and behaviours within networks can help us understand the effects of patronage (Cornell & Grimes, 2022; Langston & Cornejo, 2022; Oliveros, 2021)

The importance of governance networks comes from the need to solve collective action problems and overcome the challenges of fragmentation. Creating and maintaining collaborative ties thus requires the institutions, the power incentives, and behaviours to mitigate collective action dilemmas and achieve successful bargaining outcomes and agreements with other stakeholders. When decision-makers with strong political capital have the right incentives, they can leverage their position, political capital, and networking skills to promote collaboration. Network governance research has shown that political and institutional knowledge (i.e., knowledge about the government and governance system as a whole, the actors, available resources, etc.) can give actors a comparative advantage (in this case, to patronage appointees compared to tenured, professional bureaucrats) in creating ties with other actors (Berardo & Lubell, 2016; Morrison et al., 2023; Rittelmeyer et al., 2024; Vantaggiato & Lubell, 2022)

Because of the relatively frequent turnover, political appointees may get to know different agencies, relevant people, and organisations. They can become governance generalists, which network governance has identified as critical in facilitating collaboration. Additionally, because the higher ranks of the bureaucracy are crucial for government performance and outcomes in democratic systems with some degree of electoral competition, re-election-seeking politicians have the incentives to hire skilled individuals for these positions. Indeed, recent research on Ghana shows that politicians selectively appoint more skilled individuals to key government positions and lower-skilled individuals to less relevant posts (Brierley, 2021).

In parallel, public administration research has shown that managerial mobility (a manager moving from one position in one government to another) can promote innovation and policy adoption by aligning policy preferences. It also helps reduce transaction costs because generalists tend to know the characteristics of the other actors and the system better, which lowers uncertainty. Their career paths shape their behaviour. Their experience endows them with informal knowledge and institutional access to structural power that can be used to promote interorganisational cooperation. Thus, in this case, managers who, because of their political careers, have been appointed to several different positions in different jurisdictions have the experience and informal leavers to promote the establishment of links between the agencies more easily (Huang & Berry, 2021; Teodoro, 2009, 2010; Vantaggiato & Lubell, 2022). While my argument is not that all patronage appointments in key directive positions will be generalists, I argue that politicians have incentives to hire skilled, well-connected individuals at these levels of the bureaucracy.

Similarly, appointees with the mentioned characteristics, because of their career incentives, might find collaboration with other agencies in alignment with their job strategies. If experienced generalists, politically appointed managers are endowed with the reputation and social capital built thanks to the previous repeated interactions with other multiple actors in the system. As mentioned before, networks depend on the process of building social capital, which reduces the transaction costs and the uncertainty of potential discoordination or defection (Bodin, 2017; Lubell, 2013; Ostrom, 1990). Experienced political appointees can use their personal social capital and reputation to favour organisational collaboration with other stakeholders. Furthermore, acting as network facilitators overlaps with the career incentives of political appointees. Their career expectations, as it is usually subject to their patrons' political and electoral success, require them to strengthen and widen their professional and political network. Networking for collaboration becomes a strategy to build or advance their reputation and improve their future career prospects (Ingold & Leifeld, 2016; Teodoro, 2010).

Henceforth, when patronage appointees have ample professional and political resources, they might use their discretion to initiate collaborations, increasing the probability of a public organisation participating in collaborative projects. However, this relational capital might not always be beneficial if patronage also distorts other key bureaucratic attributes that are important for the emergence of collaborative networks.

2.2. Patronage, policy knowledge, and bureaucratic capacities

Increasing bureaucratic turnover

Increased bureaucratic turnover has been documented as stylised fact resulting from election winners reshaping the bureaucracy upon taking office (Akhtari et al., 2022; Brassiolo et al., 2020; Toral, 2024). In countries with highly politicised bureaucracies, political turnover increases the rate and intensity of bureaucratic churn at all levels of the public sector, as politically motivated personnel leave office anticipating conflicts with the incoming incumbents and elected officials (re)fill the public ranks with their network of supporters (Brassiolo et al., 2021; Doherty et al., 2019).

The heightened bureaucratic turnover produced by patronage increases the organisational instability, hence disrupting the organisational learning and organisational memory (Bagchi & Chakrabarti, 2021; Bukari Zakaria & Mamman, 2015; Pollitt, 2009; Rao & Argote, 2006; Stark, 2019; Stark & Head, 2018). As organisational theory has shown, policy knowledge is the result of collective processes and dynamics defined by the bureaucracy's organisational characteristics and capacities. At the organisational level, to be able to learn, produce, and remember knowledge, technical capacity and organisational stability are crucial (Corbett et al., 2018; Geys et al., 2023; Stark & Head, 2018).

Network emergence and evolution are dependent on the processes of continuous experimentation and learning. This means that collaboration requires policy actors to develop institutional and technical knowledge together, through repeated interactions among stakeholders and policy issues. Repeated interactions also boost trust and problem-solving capacity, which is needed for cooperation to succeed (Gerlak et al., 2019; Howlett et al., 2017; Rittelmeyer et al., 2024; Sandström et al., 2021; Siciliano, 2017; Vantaggiato, 2019). Network governance theory has frequently suggested that systems need some degree of institutional stability in order to survive and improve the governance and management of goods and services. Stability allows for the development of shared knowledge and learning (Lubell, 2013; McGinnis et al., 2020). When the bureaucracy is more unstable because it is not isolated from political turnover, the ability of repeated interactions to create trust can diminish. Instability also makes bureaucracies less likely to make credible commitments and thus less reliable as collaboration partners.

Furthermore, as a specific type of policy instrument (Scott & Thomas, 2017), establishing collaborative ventures also requires the assimilation of standardised tasks and bureaucratic routines. The development of trust and shared policy knowledge requires the predictability of actor’s actions. However, frequent organisational churn prevents this from happening. Patronage appointments, as opposed to a typical professionalised Weberian bureaucracy, exhibit higher rates of institutional memory loss, meaning a lower capacity to develop and maintain a stable schedule of activities across time and higher decision-making uncertainty (Pollitt, 2009). The ability of bureaucracies to produce and maintain knowledge is a requirement for the stability and sustainability of collaboration (Corbett et al., 2018; McGinnis et al., 2020). For these reasons, the creation of new ties and the continuity of old ones are less likely to occur because the institutional memory and the shared knowledge about the system and the policy issues are more easily lost or not credibly encouraged.

The loyalty vs competence trade-off

Patronage literature has paid significant attention to the "ally principle", according to which politicians prefer to hire loyal servants to guarantee their alignment and direct accountability to power (Dahlström & Lapuente, 2022). Patronage appointees tend to be party professionals, brokers or political agents who are well-connected through social, professional, and political networks (Panizza et al., 2019). Indeed, preference for loyal staff typically comes at the price of reducing competence and discouraging investment in policy knowledge specialisation (Dahlström & Lapuente, 2022; Gallo & Lewis, 2011; Lewis, 2008; Bendor et al. 2001).

Collaboration requires discussing and producing specialised policy knowledge among participants, conducing to the decision of the most appropriate course of action or the implementation of complex policy decisions. Network and collaborative governance literatures have long insisted on the crucial role of knowledge. Knowledge is the "currency of collaboration" (Emerson et al., 2012, p. 16). Collaboration encompasses sharing, generating, and refining knowledge to improve the ability of policy actors to create common solutions to collective issues. This involves organising and synthesising data about the system, the different stakeholders, and the policy issues, to develop a deeper understanding of the potential strategies, the interdependencies, and the capability for informed decision-making (Agranoff & McGuire, 2001; Ansell & Gash, 2008; Emerson et al., 2012; Emerson & Gerlak, 2014; Klijn & Koppenjan, 2012, 2006).

Staffing the bureaucracy with loyal servants that lack policy-domain knowledge and have safeguards to "speak truth to power" (Dahlström & Lapuente, 2022), can imply a general reduction in the technical capacity of the bureaucracy to produce and process specialised policy knowledge. As public management literature has shown, high levels of patronage can discourage investing in specialised knowledge and even reduce the motivation of tenured bureaucrats to devote effort to their work (Fuenzalida & Riccucci, 2019; Gallo & Lewis, 2011). This is a crucial issue because policy networks often operate around wicked problems like climate change, where complex domain interlinkages accompany high uncertainty about the causes and consequences of the issues. Thus, networks benefit from high levels of technical expertise and specific field experience that can reduce the risks of failure-prone experimentation and increase the chances of policy learning (Leach et al., 2013). Experts are crucial in defining policy objectives (Lubell et al., 2020) and reducing potential coordination issues (Calvert, 1992). Their presence in policy forums enhances the focus on pre-established issues, leading to more effective discussions and concrete actions (Ansell et al., 2020; Vantaggiato & Lubell, 2022). This policy knowledge also provides decision-making legitimacy and is usually guaranteed by a cadre of meritocratically appointed personnel.

For these reasons, low levels of policy knowledge and technical capacity in a public organisation, caused or deepened by an incumbent's preference for loyal over competent servants, can be detrimental to unfolding collaborative ties. In policies for which technical credibility is important, actors might avoid collaborating with organisations that do not have particular domain knowledge, as transaction costs, coordination, and defection risks are higher. I thus argue that the potentially positive effects of patronage on collaborative behaviour might be eroded by the reduction of the bureaucratic capacity brought about by hiring loyal clients over competent officials. Arguably this effect is more likely expected when loyal, policy-illiterate appointees are made at the levels of the bureaucracy at which the type of knowledge is most valuable—usually at the bureaucratic ranks in charge of the operational and implementation tasks.

3. Institutional context: Environmental governance networks in Colombia

To test my theory, I study the collaborative networks of environmental governance in Colombia. Although it is a unitary state, Colombia has been a pioneer in Latin America regarding the decentralisation of environmental governance (ONU Medio Ambiente, 2018). The country has a complex structure of authorities distributed across three primary levels of government: central government, *departamentos* (regional governments) and local governments. There are ten national-level environmental authorities, 27 *departmentos*, and 1103 municipalities. Both *departamentos* and municipalities are the main regional and local environmental authorities, respectively. In addition to these main levels, 34 environmental authorities operate at the subregional level (which can include the jurisdiction of several municipalities and territories that are part of several *departamentos*). These subregional authorities are usually in charge of co-managing the natural resources that cut across jurisdictions, along with *departamentos* and local governments. They also fulfil a crucial role in supporting local governments with limited resources to perform their environmental management responsibilities. Finally, there are six metropolitan areas that are formally constituted inter-municipal governments, which typically encompass the municipalities that are part of an urban conglomerate. These metropolitan governments act as environmental authorities in the jurisdictions of the municipalities that compose them.

Indeed, following these trends, Colombian governments have widely experimented with networked and collaborative forms of environmental management that include both public, private, and non-governmental actors. Experimentation with these forms of governance began with the decentralisation and devolution process implemented by the Constitution of 1991 and has been expanded through different legal reforms passed during the last 20 years. While most environmental policymaking happens at the local level, the heterogeneous distribution of state capacity and the extensive existence of natural resources and ecosystems that cover the country, impose the need for frequent inter-jurisdictional action and the cooperation of the multiple levels of government.[2] Joint actions between public agencies are usually formalised through a form of public contract called *convenio interadministrativo*, which requires the mutual consent and commitment of resources from the parties involved. These contracts are entirely voluntary and resemble the characteristics of intergovernmental agreements used by US agencies. They are a formal part of the public

[2] Colombia is home to some of the most important natural ecosystems (e.g., the Amazon rainforest) and is the second most megadiverse country in the world. Nonetheless, around half of the ecosystems are in critical or endangered state (WWF, 2017), and there are rapid patterns of urbanization. While around 80% of the country is rural, approximately 80% of the population lives in cities. Additionally, the national economy is highly dependent on minerals and fossil fuels exports—around 40% of exports—while also being a significant producer of renewable energies, chiefly hydroelectric—around 67% of the national energy production (Ministry of Finance, 2023).

procurement system and are subject to strict legal monitoring and enforcement by the fiscal authorities.

With regards to the public sector, Colombia can be characterised as a paradigmatic case of Latin American public administrations—deeply influenced by the Napoleonic tradition—where both the professionalisation of the public service career and flexibilisation personnel contracting have been extensively implemented, and politicisation is a pervasive feature (Ayala-García et al., 2022; Sanabria-Pulido & Leyva, 2022). Colombian public sector, similar to other Latin American and emerging democracies in the global South (Donadelli et al., 2020; Dussauge Laguna, 2011; Eakin et al., 2011; Zarychta et al., 2020), is defined by a mix of layered public sector reforms that allow for considerable variation in the public personnel hiring and firing (Sanabria-Pulido & Leyva, 2022).

Civil service career bureaucrats, across all levels of government, are selected via a competitive, merit-based process, *concurso público de méritos*, conducted by the national government. All tenured career positions in national, regional, and local agencies are selected through this *concurso*. At the same, elected officials have the authority to make discretionary appointments, referred to as *libre nombramiento y remoción* (free appointment and removal), within their jurisdiction. These are at-will hires typically made for managerial and high-level positions but can also extend to lower levels of the bureaucracy. While some of these positions have minimal qualification requirements, they are commonly regarded as political appointments and are used by incumbents to employ allies or supporters in their governments. These *libre nombramiento y remoción* appointments are the ones I will use here to measure patronage. Although most agencies at all layers of government have at least one of these at-will officials, the ratio of tenured professional bureaucrats to political at-will staff is highly heterogeneous across the country, with some agencies having fewer than 10% of the latter, and smaller agencies often predominantly composed of political appointees. I leverage this organisation-level variation to study how different patronage levels affect the likelihood of public. Even within the same metropolitan area, each municipality can have widely different proportions of tenured and at-will public employees.

Given this institutional context, I propose that Colombia serves as a typical case for studying networks of collaborative environmental governance in a polycentric system, embedded within a highly politicised public administration. This context—marked by the coexistence of professional and politicised appointments and highly uneven state resources—offers insights that are transferable to other Global South countries experimenting with similar governance mechanisms while still consolidating a strong professionalised bureaucracy.

4. Data and methodology

I leverage several administrative datasets from different public sources to identify the collaborative networks and the characteristics of the bureaucracy in Colombia. Firstly, I used the full record of contracts signed by public entities between 2018 and 2024 in the national procurement system, SECOP II.[3] Each entry contains details such as contract type, parties, value, and description. From nearly four million contracts, I used quantitative text analysis to identify all the collaborative agreements (*convenios interadministrativos*) related to environmental and natural resource management ($N = 4716$). These agreements, signed across all levels of government, define the ties in the collaborative network.[4] Collaborations include a wide range of policy tools and tasks, including joint management of resources, specialised knowledge and information exchange, infrastructure building, among others. The dataset also considers different subareas of the environmental domain, namely, ecosystems and biodiversity protection, water and forest management, climate change adaptation and mitigation, drinking water, sanitation and waste management, sustainable agriculture, mining and energy.

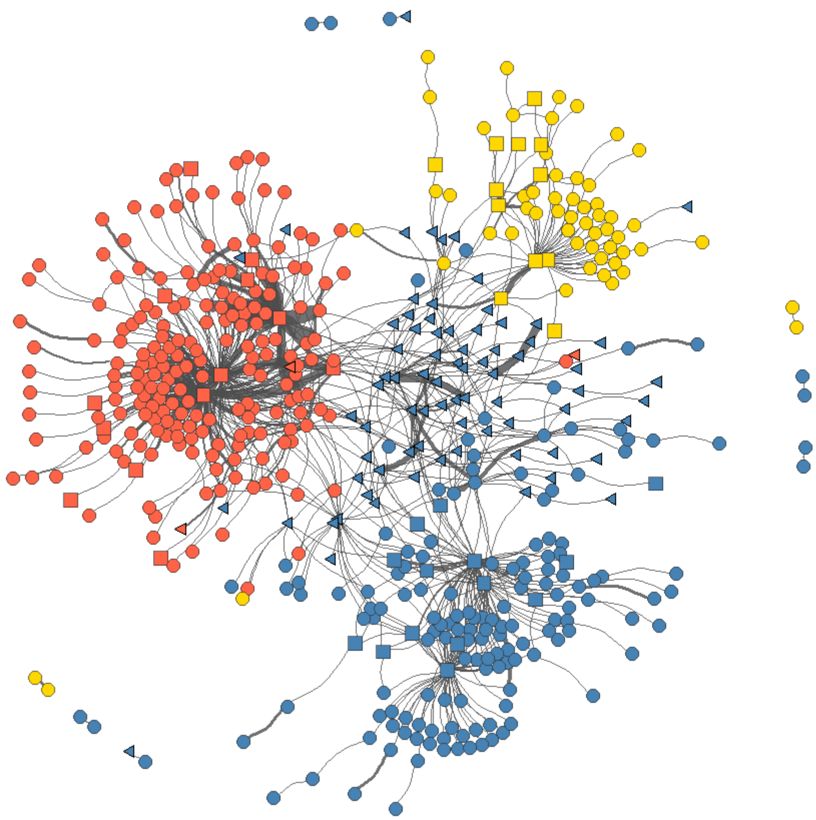
From these data, I construct a national, undirected network of environmental collaborations, where nodes are public agencies and ties are defined as the formal bilateral agreements between them. Having at least one collaborative agreement related to environmental issues between 2018 and 2024 with another public agency then defines the main boundary of the network (Berardo et al., 2020). Agencies include municipalities, *departamentos*, national ministries, public universities, research centres, development agencies, and utility companies, among others. While the network is defined by observed agreements, I also include the universe of agencies with a legal mandate in environmental governance that did not sign contracts during the period, representing them as isolates. This prevents bias from conditioning the analysis only on observed collaborations. A limitation of these data is that they capture only formal agreements, leaving informal cooperation unobserved. Yet, given Colombia's administrative tradition, in which even minimal exchanges are typically formalised in contracts, *convenios interadministrativos* offer a strong proxy for inter-agency collaboration.[5] Figure 1 depicts a subsample of the network including only organisations from the three largest *departamentos*, Cundinamarca (including Bogotá), Antioquia and Valle del Cauca.

For the analyses, I use a binary network where two organisations are considered connected if they have signed at least one collaboration agreement. The resulting graph contains 1804 organisations (nodes) and 1949 ties (edges). A large share of agencies, 592 (33%) are isolates with no observed collaborations. Network density is extremely low at 0.0012, meaning that only a small fraction of all possible ties is present. Agencies have an average 4.32 agreements (SD = 12.82), a median of 2, and the degree distribution is extremely right-skewed (skewness = 10.98), indicating that most agencies participate in very few collaborations while a handful act as hubs. The clustering coefficient is 0.033, which means that only 3.3% of potential triads are closed, reflecting minimal transitivity. Overall,

[3] All public agencies are required to report every contract they sign to SECOP II, which is subject to strict monitoring and enforcement. The complete and up-to-date record, including links to the legal documents that support the contracts, is publicly available at: https://www.datos.gov.co/Gastos-Gubernamentales/SECOP-II-Contratos-Electr-nicos/jbjy-vk9h/about_data
[4] Appendix 1 contains the detailed description of the contract data collection, processing and classification.
[5] Informal collaboration mechanisms are, of course, recognised as important for the system's dynamics (Hawkins et al., 2016; Song et al., 2019). However, I argue that these observed legal mechanisms are the formal result of other more informal exchange processes and allow to understand, with a high level of precision and comparability, the existence and extent of collaboration.

these descriptive statistics show that the network is highly sparse, dominated by isolates and a few central actors, a structure consistent with preferential attachment dynamics.

Figure 1. Environmental Collaboration Network (Top three *departamentos*)



Note: The graph shows a subnetwork of organisations from the three largest *departamentos* in Colombia: Cundinamarca (including Bogotá, blue), Antioquia (red), and Valle del Cauca (yellow). Node shapes indicate the tier of government—local (circle), regional (square), and national (triangle). Edge thickness reflects the number of collaborations between two organisations (thicker = more collaborations). Isolate nodes were removed from the graph to improve clarity (but not from the analysis).

I match these network data with the Public Employment Information and Management System (SIGEP), which records detailed information on all public employees, including demographics, education, tenure, salary, contract type, and prior experience. These data are only fully available for 2021, so I conduct a cross-sectional network analysis. To handle missing values, I rely on denoising autoencoders (Lall & Robinson, 2022), and aggregate the information at the agency level.[6]

4.1. Measurement and variables

The main independent variable of interest in this paper is patronage. As defined earlier, I measure patronage as the share of personnel in an agency appointed by an elected official, that is, the proportion of politically appointed at-will employees. Owing to the granularity of the data, I further

[6] Appendix 2 explains in detail the multiple imputation procedures and presents summaries of the imputation performance.

disaggregate this measure to distinguish between two bureaucratic ranks: the share of managerial positions filled through patronage and the share of mid-rank professional positions filled through patronage.

I also construct three measures of bureaucratic attributes that are relevant for the theory proposed here. Technical capacity is proxied by the share of employees with postgraduate education. Bureaucratic stability is measured as the mean expected tenure of personnel, derived by fitting Kaplan–Meier survival curves by contract type and projecting the expected duration of employment. Higher values indicate agencies with lower churn and greater organisational stability. [7] Finally, the social capital of appointees is proxied by the average years of experience of staff in the public sector, which reflects both institutional knowledge and embeddedness in bureaucratic networks. I consider this at the agency level and disaggregated by rank.

Several controls drawn from the governance networks literature are also included. Agency size, a well-established driver of collaboration (Krause et al., 2021; Siciliano & Wukich, 2016; Vantaggiato, 2019a), is measured by the total number of employees and entered in logarithmic form to adjust for skew. I also account for the statutory *categoría* of the jurisdiction an agency serves. This legal classification, based on population and fiscal revenues, is used by the national government to allocate transfers and responsibilities. It therefore functions both as an institutional marker of jurisdictional status and as a proxy for local fiscal capacity, similar to a GDP measure. Categories range from 1 (larger and wealthier jurisdictions) to 6 (smaller and poorer jurisdictions), with an additional "special" category for municipalities with over 500,000 inhabitants.

To capture variation in environmental pressures, I include the number of people affected by climate-related events such as floods, droughts, or landslides (inverse sine transformed). This variable proxies the *need* for collaboration: jurisdictions facing greater exposure to climate shocks should be more likely to engage in cooperative agreements (Jung et al., 2019).

I also include homophily terms that reflect institutional and political incentives (McPherson et al., 2001). A level-of-government homophily term captures collaboration across administrative tiers, where a negative coefficient would be consistent with the expectation that agencies often partner across levels to combine resources and local knowledge (Hileman & Lubell, 2018; Ostrom, 2010; Siciliano et al., 2021). An organisational-type homophily term accounts for similarity in functional mandates, where I expect collaboration to be more likely between different types of agencies. Geographic distance between agencies (inverse sine transformed) controls for the fact that proximity reduces transaction costs and increases the likelihood of shared environmental challenges (Baldwin et al., 2018; Lubell et al., 2002). A homophily term for *departamento* further captures the baseline tendency for intra-regional collaboration. Political homophily is also included, coding two agencies as aligned if staff are appointed by incumbents from the same party. Following prior research, I expect this effect to be positive, as collaboration with political allies reduces risks of defection and facilitates coordination (Gerber et al., 2013; Song et al., 2018; Henry, 2023).[8] For interpretability and

[7] Appendix 3 explains in detail the procedure used to construct this variable, summary statistics and face value tests.

[8] Appendix 4 reports summary statistics for the main variables and correlations.

to reduce collinearity, all continuous variables enter the model standardised to have mean 0 and SD = 1.

Finally, the models incorporate endogenous processes that give networks their structure. I include an *edges* term to model the baseline propensity of tie formation; given the sparsity of the network, I expect this effect to be negative. To account for clustering, I include a geometrically weighted edgewise shared partner (GWESP, decay = 0.5), which captures the well-documented tendency, the so-called triadic closure, for agencies with a common partner to collaborate as well. In governance networks, such closure reflects mechanisms of trust and risk reduction, and this term is usually positive (Berardo & Scholz, 2010). Finally, I include a geometrically weighted degree term (gwdegree, decay = 1) to model the already described skewed degree distribution, whereby some agencies attract a disproportionate share of ties.

4.2. Statistical approach

To test my arguments, I employ Exponential Random Graph Models (ERGMs) on the networks of public collaborations. Because relational data violate the independence assumptions of linear regression, linear models are not appropriate. ERGMs belong to a family of stochastic models designed precisely to analyse networks while accounting for endogenous dependencies and structural effects (Cranmer & Desmarais, 2010; Snijders et al., 2006). ERGMs specify the probability of observing a given network as a function of sufficient statistics that summarise structural features and covariate effects. Formally, for an observed network Y with adjacency entries $Y_{ij} \in \{0,1\}$, the distribution is given by

$$\Pr(Y = y \mid \boldsymbol{\theta}) = \frac{\exp\{\boldsymbol{\theta}^{\top} \boldsymbol{s}(y)\}}{\kappa(\boldsymbol{\theta})} \tag{1}$$

Where $\boldsymbol{s}(y)$ includes statistics such as density and transitivity, and covariate effects like agency capacity or political alignment; $\boldsymbol{\theta}$ is the corresponding parameter vector; and $\kappa(\boldsymbol{\theta})$ is the normalising factor ensuring a proper probability mass function. Since $\kappa(\boldsymbol{\theta})$ is computationally intractable in anything but very small networks (Hunter et al., 2012), it is approximated using simulation-based methods. Conceptually, ERGMs can be viewed as logistic regressions of tie formation, where the probability of a collaboration between two agencies depends on the changes in the specified network statistics (Desmarais & Cranmer, 2012). This formulation captures the endogenous dynamics of inter-organisational collaboration, such as clustering around shared partners or the preferential attachment to already central organisations.

The standard ERGM assumes homogeneity across actors once covariates are included. However, this assumption is unrealistic in Colombia, where agency behaviour is strongly conditioned by the country's institutional and administrative structure. Although highly decentralised, Colombia is a unitary state with a clear administrative and political hierarchy across levels of government. Regional contexts, the *departamentos*, play a decisive role in shaping public agencies' behaviour. Regional variation in administrative capacity, resource distribution, subnational political dynamics, and traditions of coordination generates systematic differences in how agencies form ties. For instance, in *departamentos* such as Antioquia or Córdoba, long-standing traditions of political coordination between regional and local governments have fostered strong collaboration among municipalities within each region. Thus, even if the networks are decentralised, they display a nested regional structure (as can be seen from Figure 1). Ignoring this structure risks attributing regional heterogeneity to general network effects, thereby conflating local institutional variation with endogenous network processes and potentially leading to bias (Duxbury & Wertsching, 2023).

To address this challenge, I develop an extension to ERGMs that explicitly accounts for regional-level heterogeneity while still modelling the network as a whole. The methodological contribution of this paper lies in adapting the iterative procedure proposed by Kevork and Kauermann (2022) for estimating mixed ERGMs (mERGMs, henceforth) with nodal random effects and generalising it to allow for group-level random effects. This allows me to fit hierarchical mERGMs to a single large national network, with random intercepts that capture the shared collaboration propensity of agencies within the same *departamento*. In this way, the model introduces partial pooling across regions, preserving the national scope of analysis while allowing systematic subnational variation to be incorporated.

Some scholars have proposed other approaches to model group heterogeneity in an ERGM framework.[9] Of particular interest here is Box-Steffensmeier et al's (2018) frailty ERGM (FERGM), which introduces nodal random effects (analogous to frailty terms in event history models) to capture unobserved propensities to form ties. While the FERGM can easily accommodate group-level heterogeneity, its estimation relies entirely on a pseudolikelihood approach, which produces biased estimates of the structural coefficients $\boldsymbol{\theta}$ (Schmid & Desmarais, 2017; Kevork & Kauermann, 2022). Kevork and Kauermann (2022) overcome this limitation by proposing an iterative strategy that combines pseudolikelihood estimation of the nodal random coefficients with simulation-based maximum likelihood (MCMLE) estimation of the structural parameters.[10] Building on this procedure, my extension introduces group-level random effects.

The choice of regional rather than nodal random effects is justified on both substantive and pragmatic grounds. Substantively, as mentioned above, many of the institutional drivers of collaboration, such as hierarchical authority, political incentives, and the distribution of resources, are organised at the *departamento* level. Pragmatically, aggregating heterogeneity to this level reduces the dimensionality of the random effect structure, making estimation feasible in a network with more than three million possible dyads. Node-level random effects are prohibitively expensive

[9] For instance, hierarchical latent space models (Sweet et al., 2013) or local dependence models (Schweinberger & Handcock, 2015) capture heterogeneity through latent classes, but they require block-structure assumptions that are neither necessary nor appropriate here, where the grouping variable is observed, and regional effects can be modelled directly. These models are less parsimonious, involve many more parameters, perform poorly with the large number of isolates present in this network, and often yield coefficients that are difficult to interpret when latent positions correlate with observed covariates (Cranmer et al., 2017). More standard hierarchical Bayesian ERGMs (Slaughter & Koehly, 2016) also prove unsuitable, as they assume multiple independent networks rather than a single interconnected network with group structures (Wang et al., 2013).

[10] Kevork and Kauermann's (2022) original procedure used the step length algorithm proposed by Hummel (2012), which has now been deprecated. I implement the improved MCMLE algorithm (Krivitsky et al, 2023a), which is now the standard method used in the `R` `ergm` package (Handcock et al., 2025; Hunter et al 2008; Krivtisky et al, 2023b).

to estimate in this setting, whereas modelling shared regional propensities captures the most relevant source of heterogeneity while ensuring computational tractability. I know describe my approach to estimating mERGMs.

Let $g(i)$ denote the group (*departamento* in this case) of agency $\boldsymbol{i}$. The probability of the observed network conditional on both structural parameters and *departamento* random effects is then defined as

$$\Pr(Y = y \mid \boldsymbol{\theta}, \boldsymbol{\alpha}) = \frac{exp\{\boldsymbol{\theta}^{\top}\boldsymbol{s}(y) + \sum_{i<j}\left(\alpha_{g(i)} + \alpha_{g(j)}\right)y_{ij}\}}{\kappa(\boldsymbol{\theta}, \boldsymbol{\alpha})} \tag{2}$$

This is an extension of the canonical form in eq. (1). Here, $\boldsymbol{\alpha}$ is a g-dimensional vector of group-specific random effects assumed to follow

$$\boldsymbol{\alpha} \sim N\left(0, \sigma_\alpha^2\, \boldsymbol{\mathcal{I}}_g\right) \tag{3}$$

Where σ_α^2 is the variance and $\boldsymbol{\mathcal{I}}_g$ represents a g-dimensional identity matrix. In this form, we have a mixed model, with fixed effects and group-level random coefficients. From eq. (2) we can obtain the model for each tie Y_{ij} conditional on all other ties in the network, Y_{-ij}, as follows:

$$\log\left\{\frac{\Pr\left(Y_{ij} = 1 \mid Y_{-ij}, \boldsymbol{\theta}, \boldsymbol{\alpha}\right)}{\Pr\left(Y_{ij} = 0 \mid Y_{-ij}, \boldsymbol{\theta}, \boldsymbol{\alpha}\right)}\right\} = \boldsymbol{\theta}^{\top}\Delta_{ij}\boldsymbol{s}(y) + \alpha_{g(i)} + \alpha_{g(j)} \tag{4}$$

where $\Delta_{ij}\boldsymbol{s}(y)$ is the vector of change statistics associated with toggling the edge between agencies i and j, and $\boldsymbol{\theta}$ the corresponding coefficients. By additively including the group random effects associated with each node, α_g, this formulation captures unobserved heterogeneity at the regional level, such that agencies within the same *departamento* share a baseline propensity to collaborate, while still allowing for endogenous dependencies to be modelled through standard ERGM terms.

Kevork and Kauermann (2022) propose an iterative procedure in which the random effects $\boldsymbol{\alpha}$ are first estimated independently via a Laplace approximation and then supplied to the ERGM as fixed offsets to facilitate simulation-based maximum likelihood estimation of the structural parameters $\boldsymbol{\theta}$. The random effects are then updated through pseudolikelihood using the current estimate of $\boldsymbol{\theta}$, and the two steps are repeated until convergence.[11] In practice, the estimation of $\boldsymbol{\alpha}$ is implemented in R using the `mgcv` package (Wood, 2011), while the ERGM step is performed in the **`ergm`** package (Hunter et al., 2008). This strategy yields a tractable and numerically stable approach for fitting mixed ERGMs, and I adapt it to estimate a hierarchical version with group-level random effects in my national network.[12]

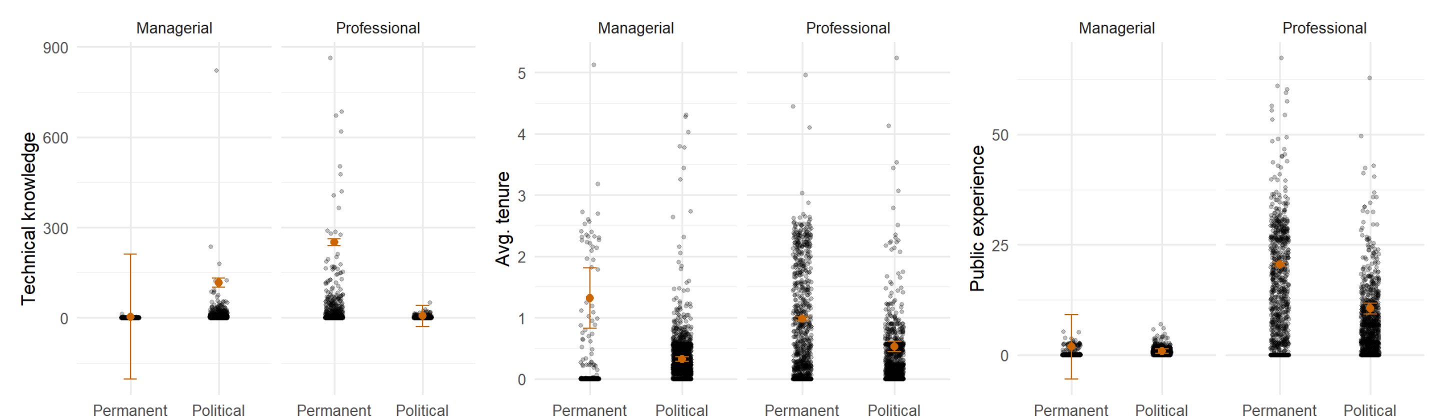
[11] All models converged within 23 to 26 iterations. Appendix 5 presents graphical evidence of the robustness of the estimation procedure for both random effects and structural coefficients.
[12] Appendix 7 compares the results, Goodness-of-Fit and AICs of the mERGM specifications against the standard ERGM specifications

5. Results

5.1. Do political appointees differ from permanent bureaucrats?

Before turning to the mERGM results, I document baseline differences between political appointees and permanent (career) staff at the managerial and professional ranks. Figure 2 shows the distribution of organisation-level values for each bureaucratic attribute, overlaid with estimated group means and 95% CIs within each (rank × type of appointment) cell. Figure 3 reports the within-rank difference (political appointees minus permanent) with 95% CIs; points below (above) zero indicate lower (higher) values among political appointees.

Figure 2. Organisation means by rank and type of appointment

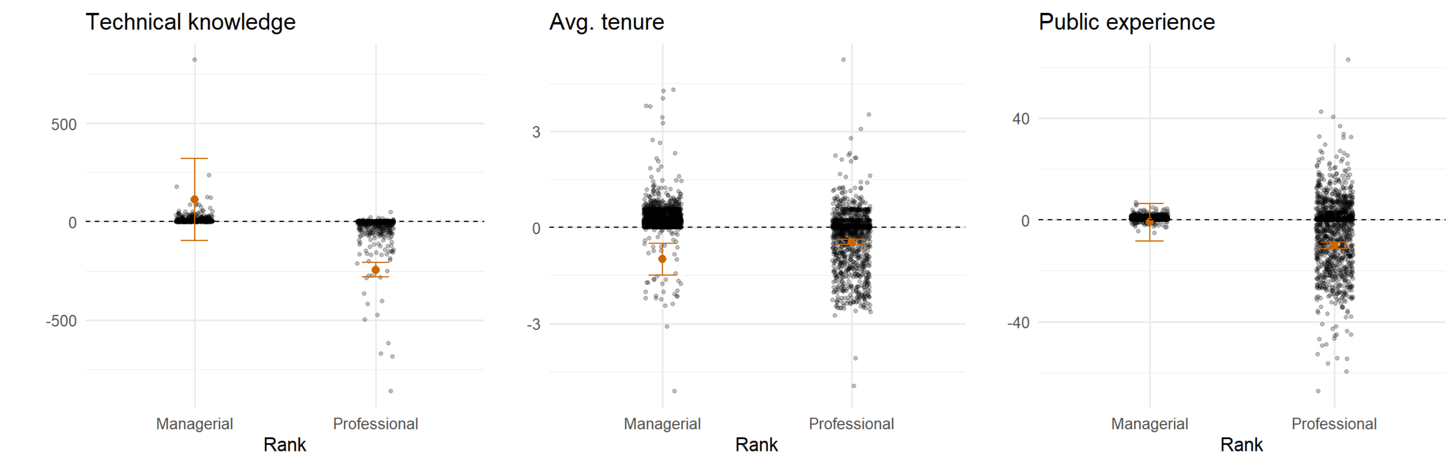


Note: Estimated group means and 95% CIs in orange. CIs that exclude 0 indicate statistically significant effects

These descriptive results show consistent and substantively meaningful patterns. For technical knowledge, measured as people with a postgraduate degree, managers show no clear difference between political appointees and permanent staff, whereas among professional-level bureaucrats, appointees are systematically less qualified. For stability, appointees have shorter tenures at both ranks, consistent with greater churn under patronage. Finally, regarding public-sector experience, the proposed proxy for social and political embeddedness, there is no clear evidence of differences between politically appointed and permanent managers; at the professional level, permanent bureaucrats do exhibit significantly more public sector experience than their patronage counterparts in that rank.

These descriptive patterns mirror the stylised facts of patronage outlined above. First, patronage appointees tend to have shorter tenures. Second, the loyalty–competence trade-off is evident in the selection of appointees, particularly at mid-level ranks. However, incumbents appear to exercise greater care in filling managerial posts, as political and permanent top bureaucrats show no clear differences in their technical qualifications or public sector experience.

Figure 3. Within-rank differences (patronage appointments vs permanent staff)



Note: Estimated group means and 95% CIs in orange. CIs that exclude 0 indicate statistically significant effects. Points below the zero line indicate higher values of the attribute for permanent career staff.

5.2. Main network models

Table 1 reports the mERGM coefficients for the main model specifications. As in a logistic regression, coefficients can be exponentiated and interpreted as multiplicative effects on the odds of a tie (Levy et al., 2016; Scott & Greer, 2019). The first column presents the baseline model with only structural terms and controls (Lusher et al., 2013). Model 2 adds the aggregate patronage measure and bureaucratic attributes. Models 3 and 4 disaggregate these variables by managerial and professional ranks, respectively, while Model 5 includes both simultaneously. I first interpret the control and endogenous structural variables and then turn to the main variables of interest.

Table 1. Main results: mixed Exponential Random Graph models with *departamento* REs

	Baseline Model	Model 2	Model 3	Model 4	Model 5
Aggregate measures					
Patronage		-0.008			
		(0.040)			
Technical capacity		-0.184***			
		(0.035)			
Stability		-0.902***			
		(0.048)			
Public experience		1.046***			
		(0.050)			
Managerial-rank measures					
Managerial patronage			0.155***		0.175***
			(0.035)		(0.035)
Managerial technical capacity			-0.253***		-0.199***
			(0.037)		(0.038)
Managerial stability			-0.503***		-0.512***
			(0.040)		(0.042)

Table 1. Main results: mixed Exponential Random Graph models with *departamento* REs

	Baseline Model	Model 2	Model 3	Model 4	Model 5
Managerial public experience			0.424^{***} (0.032)		0.412^{***} (0.032)
Professional-rank measures					
Professional patronage				-0.354^{***} (0.037)	-0.359^{***} (0.039)
Professional technical capacity				-0.167^{***} (0.040)	-0.212^{***} (0.040)
Professional stability				-0.102 (0.071)	0.038 (0.072)
Professional public experience				0.128 (0.067)	0.044 (0.068)
Controls					
Staff size	1.687^{***} (0.026)	1.674^{***} (0.030)	1.757^{***} (0.027)	1.696^{***} (0.030)	1.735^{***} (0.030)
People affected by climate-events	-0.946^{***} (0.022)	-0.964^{***} (0.022)	-0.948^{***} (0.023)	-0.925^{***} (0.021)	-0.908^{***} (0.022)
Government tier: Local	-2.396^{***} (0.083)	-2.276^{***} (0.084)	-2.426^{***} (0.084)	-2.416^{***} (0.083)	-2.451^{***} (0.086)
Geographical distance	-0.733^{***} (0.037)	-0.743^{***} (0.037)	-0.736^{***} (0.038)	-0.739^{***} (0.037)	-0.736^{***} (0.036)
Category (base group: Special)					
Category 1	-4.348^{***} (0.072)	-4.592^{***} (0.074)	-4.390^{***} (0.077)	-4.320^{***} (0.071)	-4.350^{***} (0.076)
Category 2	-3.792^{***} (0.077)	-3.852^{***} (0.080)	-3.952^{***} (0.076)	-3.810^{***} (0.077)	-3.959^{***} (0.078)
Category 3	-4.864^{***} (0.111)	-5.001^{***} (0.118)	-4.985^{***} (0.114)	-4.791^{***} (0.113)	-4.881^{***} (0.115)
Category 4	-5.065^{***} (0.150)	-5.334^{***} (0.151)	-5.151^{***} (0.154)	-5.143^{***} (0.153)	-5.187^{***} (0.154)
Category 5	-4.833^{***} (0.213)	-5.240^{***} (0.213)	-4.995^{***} (0.218)	-4.776^{***} (0.212)	-4.940^{***} (0.213)
Category 6	-4.832^{***} (0.104)	-5.231^{***} (0.109)	-4.970^{***} (0.109)	-4.733^{***} (0.104)	-4.808^{***} (0.109)
Homophily terms					
Homophily: Government Tier	-0.341^{***} (0.075)	-0.303^{***} (0.076)	-0.368^{***} (0.075)	-0.347^{***} (0.074)	-0.367^{***} (0.071)
Homophily: Organisation Type	-1.775^{***} (0.145)	-1.797^{***} (0.150)	-1.745^{***} (0.138)	-1.729^{***} (0.143)	-1.721^{***} (0.144)
Homophily: Political Party	1.534^{***} (0.092)	1.558^{***} (0.096)	1.529^{***} (0.095)	1.565^{***} (0.093)	1.554^{***} (0.092)
Homophily: *Departamento*	2.621^{***} (0.083)	2.670^{***} (0.086)	2.613^{***} (0.086)	2.600^{***} (0.084)	2.589^{***} (0.084)
Endogenous structural terms					
Degree distribution (GWDEG)	3.935^{***} (0.121)	4.042^{***} (0.124)	4.058^{***} (0.124)	4.030^{***} (0.125)	4.115^{***} (0.126)

Table 1. Main results: mixed Exponential Random Graph models with *departamento* REs

	Baseline Model	Model 2	Model 3	Model 4	Model 5
Transitivity (GWESP)	-0.127^{***} (0.024)	-0.128^{***} (0.024)	-0.131^{***} (0.025)	-0.129^{***} (0.025)	-0.132^{***} (0.025)
Edges	-1.838^{***} (0.129)	-1.601^{***} (0.156)	-1.700^{***} (0.140)	-2.072^{***} (0.136)	-1.981^{***} (0.145)
AIC	27891	26241	26715	26122	22557
Adjusted AIC	15614	16829	15756	15588	15427
REs	32	32	32	32	32
$\sigma_{\text{Departamento}}$	2.53	2.74	2.62	2.56	2.61
Pseudo-ICC	0.21	0.22	0.21	0.21	0.21

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Coefficients are the conditional log-odds change in the probability of a tie. Standard deviation in parentheses. All continuous variables are z-standardised to have mean 0 and SD 1. The $\sigma_{(\text{Departamento})}$ is the standard deviation of the estimated region-level random effects on the log-odds scale. Pseudo-ICC is the share of residual variance in tie formation attributable to between-region clustering. Appendix 6 explains in detail how these parameters are calculated. AIC is the standard Akaike Information Criterion as calculated by the **ergm** package. The adjusted AIC is computed via network simulation with a penalty for the effective degrees of freedom of the group random effects. Appendix 7 explains this adjustment and compares the results. Table A 7 also presents VIFs for the variables in the fully saturated model 5 to assess collinearity.

The structural parameters behave largely as expected. The positive and very large coefficient for the degree distribution term (GWDEG, ~3.9–4.1) indicates a strong propensity toward degree heterogeneity, i.e., the presence of hubs that maintain disproportionately many collaborative ties. By contrast, the transitivity parameter (GWESP) is consistently negative (~-0.13), suggesting collaborations are less likely to occur in closed triads than in more diverse, non-redundant configurations. Finally, the negative and significant coefficient for the edges term (~-1.6 to -2.1) reflects the overall sparsity of the network, with a baseline probability of a tie of only around 13–14%.

Control variables are stable across models. Larger agencies are significantly more likely to collaborate: a one-SD increase in staff size (~773 employees) is associated with a log-odds increase of 1.69, implies more than a fivefold increase in the odds of a tie ($\exp(1.69) \approx 5.4$). This is consistent with expectations that greater bureaucratic capacity enables collaboration (Sanchez et al., 2024). This resonates with the results for proxy for jurisdiction size and wealth (*category*): agencies in the most deprived constituencies (category 6) are roughly 99% less likely to collaborate than those in the wealthiest “special” jurisdictions ($\exp(-4.83) \approx 0.008$). Contrary to expectations, climate pressures strongly reduce the probability of collaboration ($\exp(-0.95) \approx 0.39$), consistent with agencies in high-risk areas being less attractive or less able partners. Local-level agencies are much less likely to form ties ($\exp(-2.4) \approx 0.09$), and geographical distance, as expected, is negatively correlated with the emergence of collaborative ties ($\exp(-0.73) \approx 0.48$).

The homophily terms show that there are tendencies for cross-institutional collaboration but with preferences for regional and political similarities. Agencies are 29% less likely to partner with others of the same level of government ($\exp(-0.34) \approx 0.71$) and 83% less likely to collaborate with the same organisational type ($\exp(-1.78) \approx 0.17$). Taken together, these results can be interpreted as a preference for complementary, although likely overlapping, responsibilities and mandates.

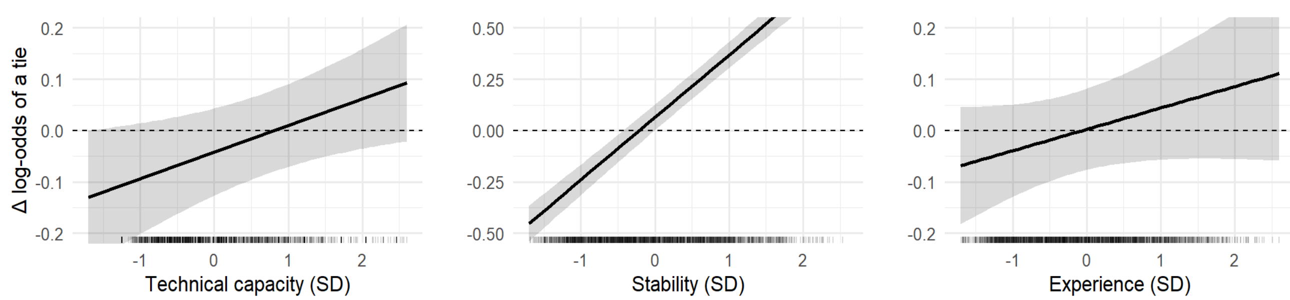
Additionally, collaborations are much more likely to happen between actors within the same region ($\exp(2.62) \approx 13.8$) and between actors whose appointments are made by incumbents of the same party ($\exp(1.53) \approx 4.6$).

The aggregate patronage measure (Model 2) is small and insignificant, but disaggregation reveals clear heterogeneities across the bureaucratic hierarchy. Managerial-level patronage is positive: a one-SD increase raises the odds of a tie by nearly 20% ($\exp(0.18) \approx 1.19$). By contrast, professional-level patronage is negative, lowering the odds of collaboration by about 30% ($\exp(-0.35) \approx 0.70$). By contrast, bureaucratic attributes display consistent and unexpected patterns. Technical capacity, proxied by the share of staff with postgraduate degrees, is consistently negative across ranks: a one-SD increase reduces collaboration odds by 15–25%. Bureaucratic stability, measured as average expected tenure, is also significantly negative both at the aggregate ($\exp(-0.90) \approx 0.41$) and at the managerial level ($\exp(-0.51) \approx 0.60$). Conversely, everything else constant, agencies with more experienced staff are more likely to collaborate, with managerial experience rising the odds by about 50%. At the professional level, stability and experience have small, insignificant effects.

5.3. Interaction models

To further understand how the effect of patronage on collaboration varies by bureaucratic attributes, I estimated a series of interaction mERGMs. Figure 4 to Figure 6 present the marginal effects of patronage conditional on each key bureaucratic attribute. [13]

Figure 4. Marginal effects of aggregate patronage



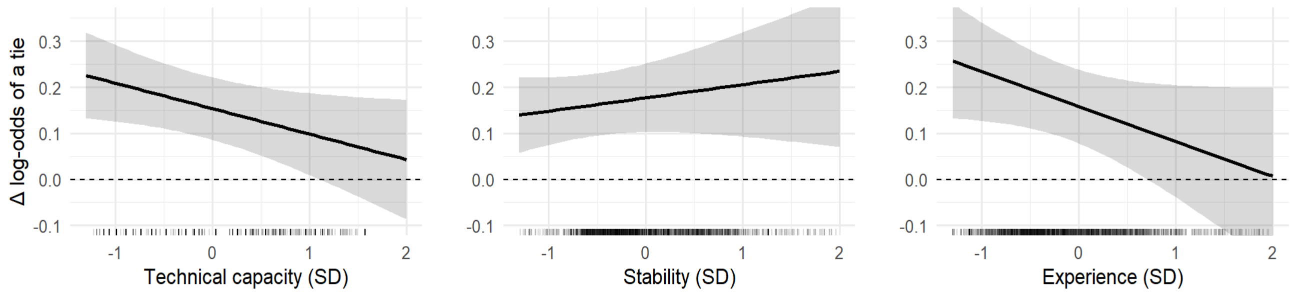
Note: Marginal effect of patronage on the log-odds of collaboration conditional on bureaucratic attributes (standardised). Lines show log-odds effects; shaded areas are 95% delta-method CIs; rugs show the distribution of the moderator. The Patronage × Technical capacity interaction term is significant at the 0.05 level; Patronage × Stability interaction term is significant at the 0.001 level; the Patronage × Public experience is not significant at the conventional levels.

While the aggregate patronage effect remains mostly statistically insignificant, the most notable result is that the effect of patronage appointments rises with higher levels of technical capacity and especially becomes significant and positive once organisations are close or above the average stability level. In other words, political appointments deliver collaboration only once a basic

[13] Table A 9 to Table A 12 in Appendix 8 present the full interaction models results.

bureaucratic platform is in place. The interaction with public experience is positive but imprecise, suggesting little extra "boost" from average experience beyond its large direct effect.

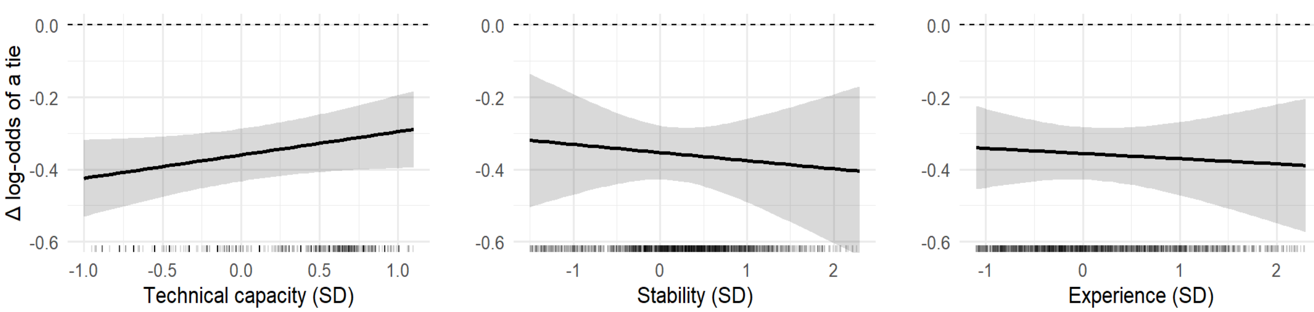
Figure 5. Marginal effects of managerial-level patronage



Note: Marginal effect per 1-SD of managerial patronage on the log-odds of collaboration conditional on bureaucratic attributes (standardised). Lines show log-odds effects; shaded areas are 95% delta-method CIs; rugs show the distribution of the moderator. Only the Managerial patronage × Managerial technical capacity interaction term is significant at the 0.05 level.

Disaggregated analyses show rank-specific dynamics. For managerial appointments, the strongest interaction is with technical capacity: the collaboration premium from politically appointed managers is largest when the managerial specialised technical knowledge is lower. This suggests a trade-off or substitution pattern between political resources and technical knowledge at top ranks. The interaction with managerial stability is small and not significant, and the weak negative interaction with managerial public experience hints that when managers are already well embedded via career experience, political connections add less at the margin. Netting out, managerial political appointments can foster collaboration, but its returns are greatest where managerial specialisation is scarcer.

Figure 6. Marginal effects of professional-level patronage

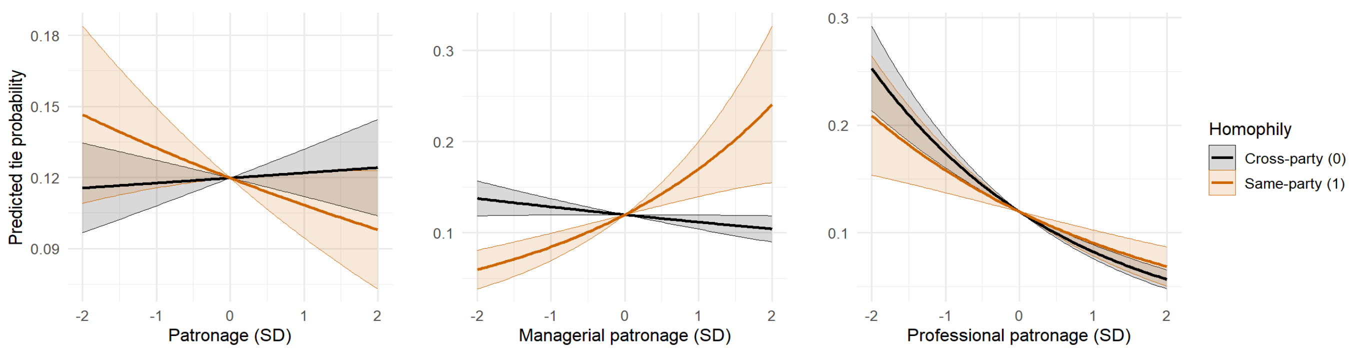


Note: Marginal effect per 1-SD of managerial patronage on the log-odds of collaboration conditional on bureaucratic attributes (standardised). Lines show log-odds effects; shaded areas are 95% delta-method CIs; rugs show the distribution of the moderator. None of the interactions are statistically significant at the conventional levels.

At the professional level, no interactions are significant (technical capacity trends positive but is not significant), indicating that the negative effect of professional patronage holds regardless of bureaucratic resources. The politicisation of operational ranks reduces the capacity to execute collaborative work, and extra capacity or bureaucratic experience does not reliably neutralise that harm.

Taken together, the results offer a more detailed picture of how bureaucratic politics shapes collaboration. Managerial patronage is associated with more collaboration, but its gains substitute for technical depth and experience—largest when managerial capacity is thin. Although there are no systematic differences in the specialised knowledge of managerial positions, as evidenced before, this can happen because the main resource political appointees can use to leverage collaboration is their political network, not their specialised technical knowledge. If that is the case, the effect of managerial patronage should be particularly strong across politically homophilous ties, i.e., it should increase the likelihood of ties among organisations aligned across party lines. I offer some additional evidence of this below, running interaction models between political homophily and patronage.

Figure 7. Marginal effects of patronage by political homophily

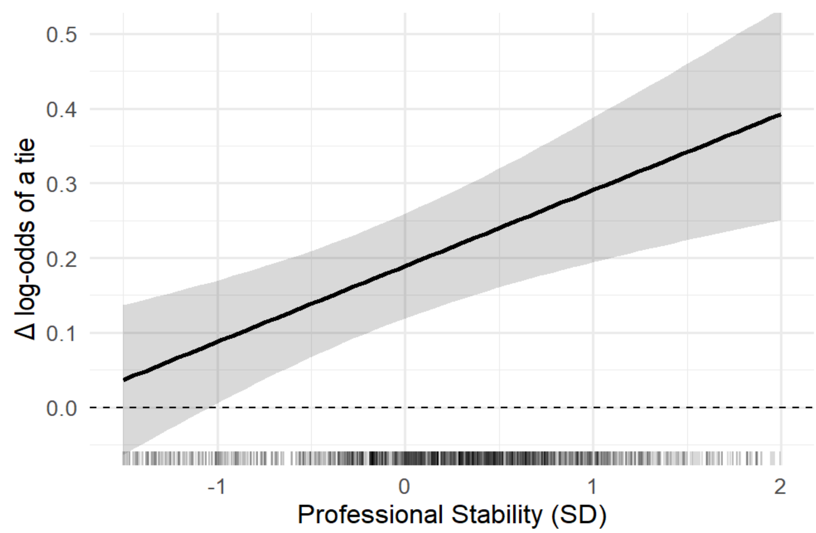


Note: Marginal effect of patronage on predicted tie probability by political homophily. Curves anchored at the overall tie probability (network density = p = 0.12%). Ribbons show 95% delta-method CIs for slope uncertainty. Only the interaction for Managerial patronage × political homophily is significant at the conventional levels.

Indeed, only managerial patronage shows a positive and statistically significant interaction with party homophily. This offers clear evidence of a co-partisan boost in collaboration caused by top political appointees. One-SD increase in managerial patronage is associated with 7% lower chances of cross-party collaborations ($\exp(-0.07) \approx 0.93$)—i.e., when political homophily = 0. Conversely, a similar increase in managerial patronage is associated with 1.5 more chances of same-party ties ($\exp(-0.07 + 0.48) \approx 1.51$). Substantively, politicised managers appear to leverage partisan channels: they facilitate ties with co-partisans but discourage or fail to build ties across party lines. Importantly, this pattern is not present for professional-level patronage or for the aggregate measure.

Finally, although the aggregate level seems to mask the rank-level nuances of patronage, the interaction effect with stability seems to suggest that once organisations are stable and (to a lesser extent) technically equipped, patronage can be leveraged into ties. The fact that this effect does not come up in the rank-level analyses can be potentially explained by cross-rank complementarities, i.e., when political managers operate on top of stable professional corps. At the organisational scale, appointees might be able to convert partisan and institutional links into actual projects because execution capacity is strong and predictable. To test this hypothesis, I interact managerial patronage with professional stability. Figure 8 plots the marginal effect of managerial patronage across levels of professional-level stability. In line with this expectation, the interaction is large and positive, meaning that professional level stability strongly boosts the ability of political connected managers to work together with other organisations. A one-SD increase in the average tenure length of professional-rank bureaucrats (~ 5.4 years) strengths the effect of patronage by roughly 11% ($\exp(0.102) \approx 1.11$). These results align with the organisational balancing thesis (Krause et al., 2006)

Figure 8. Marginal effects of patronage conditional on professional-level stability



Note: Marginal effect of managerial patronage on collaboration conditional on professional stability. Line shows log-odds effects; shaded areas are 95% delta-method CIs; rugs show the distribution of the moderator.

6. Discussion

The results reveal a complex picture of how patronage shapes the use of collaborative governance mechanisms. Whereas managerial-level appointees tend to facilitate the emergence of ties, politicised hiring at the professional level consistently undermines them. These divergent effects resonate with the discussed evidence that patronage is rarely uniform in its consequences but instead varies across bureaucratic ranks and functions, as politicians often pursue dual strategies reserving meritocratic criteria for high-skilled managerial posts while deploying patronage at lower levels to sustain partisan commitments (Brierley, 2020; Panizza et al., 2018). The Colombian case mirrors this pattern. Patronage at the top provides organisations with politically embedded actors who can mobilise resources to initiate joint projects, whereas at the operational level it introduces instability and weakens collaborative capacity.

The findings also refine the theoretical framework linking patronage to bureaucratic attributes. While I hypothesised that technical capacity, stability, and social capital would condition the effects of patronage, the results demonstrate that these bureaucratic resources are not interchangeable. After accounting for local development and agency size, agencies with stronger technical qualifications and greater stability are in fact less likely to form collaborative ties. This finding aligns with arguments that bureaucratic capacity may exhibit a curvilinear relationship with collaboration: highly capable organisations may prefer to "go it alone" and rely on their own resources rather than invest in demanding joint ventures (Krause et al., 2021; Vantaggiato, 2019a; Dahlström & Lapuente, 2022). On the other hand, public sector experience emerges as a consistent facilitator of collaboration, lending support to relational-capital arguments in network governance research (Berardo & Scholz, 2012; Siciliano et al., 2021) and the role of bureaucratic embeddedness in facilitating patronage's potential positive effects on governance outcomes.

The interaction models provide further nuance. At the aggregate level, patronage becomes conducive to collaboration only in agencies with a basic bureaucratic platform, particularly stability. Stability reduces the risks of bureaucratic churn, enabling appointees to leverage their political capital effectively. At the managerial level, the substitution between patronage and technical depth indicates that political connections can compensate for thinner expertise but lose their marginal value where managerial capacity is already high. Importantly, the positive interaction between managerial patronage and partisan homophily confirms that the primary resources political managers contribute are political and institutional connections rather than technical knowledge. Therefore, patronage boosts political homophily as key channel for coordination (Gerber, Henry & Lubell, 2013; Hawkins, 2010).

By contrast, professional patronage dampens collaboration irrespective of bureaucratic attributes. Together with the evidence about operational-level patronage appointees being less qualified and experienced, this pattern reflects the logic of low-level patronage emphasised by Brierley (2021): politicians interfere in less skilled posts because they are useful for rewarding clients but non-essential for state performance. Operational appointees lack the networks or discretion to leverage political capital for collaboration and are, potentially, less committed to policy goals due to their short tenures and clientelistic incentives (Quintero, 2025). In this sense, politicisation at the professional level reduces the capacity required for engaging and executing collaborative projects.

7. Conclusion

This paper examined how patronage appointments shape intergovernmental collaboration in Colombia's environmental governance network. The results confirm that collaboration emerges not only from administrative capacity but also from political mechanisms embedded in bureaucratic hierarchies. Whereas managerial patronage can foster collaboration by mobilising partisan and institutional networks, professional-level patronage undermines it by weakening the operational reliability of agencies. Furthermore, the analyses suggest that the coordination benefits of patronage are most effective when supported by a stable bureaucratic workforce. These effects underscore that collaboration in environmental governance is not simply a function of competence or policy alignment but is deeply conditioned by the political logics of bureaucratic dynamics.

Several limitations should be noted. First, the analyses presented here are essentially correlational and, thus, further research must be done to strengthen theory and empirical causal evidence about the relationship between patronage dynamics and collaborative governance. This is however a first attempt at connecting these two research strands that have remained otherwise separated despite the hopefully now clear entanglements. Second, the paper focused on tie formation rather than the quality or outcomes of collaboration. It is not evident from the results that the political mechanisms that enable collaboration may lead to effective environmental governance or instead reproduce political collusion and corruption without substantive policy benefits (Bersch et al., 2017; Harris et al., 2022). Building on the findings, elsewhere I evaluate the effects of collaboration on water governance outcomes at the local level (Quintero, 2025). Finally, while the study leverages detailed data on Colombian agencies, the extent to which these dynamics generalise to other policy domains and national contexts remains an open question and requires further comparative research.

More broadly, these findings contribute and expand to comparative debates on bureaucratic politics, considering its effects on collaborative governance tools. The evidence supports the view that the effects of patronage depend on where it penetrates the hierarchy (Kopecký et al., 2016; Brierley, 2022). In fragmented governance settings like Colombia, where collaboration is often indispensable to manage cross-jurisdictional issues, the balance between political capital and bureaucratic competence becomes particularly consequential. Patronage should not be conceptualised solely as an obstacle to governance. Instead, its effects are conditional on bureaucratic rank, organisational resources, and partisan alignment. Patronage can be a liability where it erodes technical capacity and stability, but it can also provide the political incentives to mobilise collaborative regimes. This duality echoes broader calls in the literature to move beyond dichotomous views of politicisation versus meritocracy and to recognise the hybrid logics through which political and bureaucratic resources interact in practice (Brierley, 2022; Dansandi & Esteve, 2017).

These findings also speak to the politics of environmental collaboration more directly. Collaborative responses to cross-jurisdictional challenges such as climate change or ecosystem management are often framed as requiring strong policy expertise and developed institutional coordination mechanisms to reduce the risks of cooperation (Carr & Hawkins, 2013; Berardo & Lubell, 2019; Swann et al., 2020; Vantaggiato & Lubell, 2022). Yet this paper shows that political mechanisms—partisan alignment, political managers' networks, and cross-rank complementarities—can serve as substitutes for administrative structures in building inter-organisational ties. Coordination, in other words, may be achieved through politics as much as through institutional design. This can help explain some of the pitfalls of collaborative governance: it is not simply a function of institutional design or bureaucratic quality, but also of how political logics permeate the bureaucracy unevenly across regions. Understanding this interplay is crucial for both theories of network and environmental governance.

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Appendices

A. Appendix 1. Data collection, processing, and classification

To build the network of collaborations among public organisations, I focus on *convenios interadministrativos*. As explained in the main text, these are flexible, voluntary contracts that public entities in Colombia use to formalise collaborations with other public organisations. These contracts are reported in the national public procurement system, SECOP II, and are subject to the same regulation and monitoring as other public procurement process. Although all contracts signed by public agencies are publicly available online, identifying which ones represent environmental inter-administrative agreements is not a straightforward task. I therefore combined manual coding with automated text classification using Large Language Models (LLMs). This section describes the process.

a. Keyword querying

The first step was to query SECOP II using keywords from the contract descriptions that in Colombian public law and administrative jargon typically denote *convenios interadminsitrativos*. The list of keywords was compiled through fieldwork and interviews with public lawyers and experienced bureaucrats, and then expanded iteratively by extracting new terms from contracts already identified. The final Spanish keyword set was: “auna” OR “coordina” OR “articula” OR “cofinancia” OR “cogestion” OR “colabora” OR “coadyuva OR “coopera” OR “unir” OR “union” OR “unifica” OR “junta” OR “concur” OR “conjunt” OR “memorando” OR “voluntad” OR “convenio” OR “interinstitucional” OR “interadministrativo” OR “alianza” OR “aunar”. After manually discarding contracts with non-public entities or unrelated purposes, this step yielded an initial dataset of 31,064 contracts signed between 2016 and 2024.

b. LLM classification: whole network

Because the keyword search was intentionally broad to maximise recall, many retrieved contracts were not relevant. To identify those specifically related to environmental collaborations, I relied on the short textual descriptions included in SECOP II and classified them with LLMs—a type of neural network based on the transformer architecture. LLMs are increasingly used by social scientists to perform a wide range of text-as-data tasks such as sentiment analysis and topic modelling (Gilardi et al., 2023; Barrie et al., 2024). LLMs are well suited to this task: they leverage self-supervised training on vast corpora and contextual word embeddings, making them effective for classifying short texts without specialised training data (Ornstein et al., 2025). Alternative approaches such as dictionary methods or topic models are less appropriate given the brevity and specificity of the descriptions. For replicability, I used open-source multilingual versions of the Mistral AI models. Because LLM validation practices are still widely discussed and lack standardisation, I adopted an iterative approach that combined prompt engineering with performance evaluation, both to enhance accuracy and to ensure transparency (for a detailed discussion on LLM replication and transparency, see Weber & Reichardt, 2024 and Barrie et al., 2024b).

i. *Prompt engineering and validation*

I first created a manually labelled "ground-truth" sample of 2,000 randomly selected contracts (environmental collaboration = 1; other = 0). This set (6.4% of the dataset) was used exclusively for prompt design, not model training. Using the Mistral Nemo 24.07 model (weights available here), I tested a zero-shot prompt and four increasingly specific few-shot prompts (in Spanish) that: (i) defined the environmental domain broadly or narrowly, (ii) enumerated relevant subsectors, and (iii) included positive and negative exemplars. Table A 1 shows the original Spanish prompts with corresponding English translations.

Table A 1. LLM classification prompts – Whole network

Version	Original prompt	English version
Zero-shot (**ZSP**)	"La siguiente es la descripcion de un convenio interadministrativo entre dos entidades publicas en Colombia. Usando tu conocimiento sobre politicas publicas, el contexto juridico y administrativo colombiano y la descripcion del contrato, tu tarea es decidir si el contrato hace referencia a temas ambientales. Responde 1 si el contrato se refiere a temas ambientales y 0 si no lo hace. Solo responde 1 o 0 y no introduzcas ni justifiques ni expliques tu respuesta"	"The following is a description of an inter-administrative agreement between two public entities in Colombia. Using your knowledge of public policies, the Colombian legal and administrative context, and the contract description, your task is to decide whether the contract refers to environmental issues. Answer 1 if the contract refers to environmental issues and 0 if it does not. Answer only 1 or 0 and do not introduce, justify, or explain your answer."
Few-shot, general reference to environmental topics (**FSP1**)	"La siguiente es la descripcion de un convenio interadministrativo entre dos entidades publicas en Colombia. Usando tu conocimiento sobre politicas publicas, el contexto juridico y administrativo colombiano y la descripcion del contrato, tu tarea es decidir si el contrato hace referencia al ambito ambiental. Por ámbito ambiental me refiero a todos los temas especificamente relacionados con la gestión ambiental, pero también en sentido amplio a los temas cercanos, incluidos mineria, energia, agricultura, desarrollo sostenible, agua potable y disposicion de residuos, etc. Responde 1 si el contrato se refiere a temas ambientales o alguno de estos temas cercanos y 0 si no lo hace. Solo responde 1 o 0 y no introduzcas ni justifiques ni expliques tu respuesta"	"The following is a description of an inter-administrative agreement between two public entities in Colombia. Using your knowledge of public policies, the Colombian legal and administrative context, and the contract description, your task is to decide whether the contract refers to the environmental field. By environmental field, I mean all issues specifically related to environmental management, but also, in a broad sense, to related issues, including mining, energy, agriculture, sustainable development, drinking water and waste disposal, etc. Answer 1 if the contract refers to environmental issues or any of these related issues, and 0 if not. Answer only 1 or 0 and do not introduce, justify, or explain your answer."
Few-shot, specific reference to environmental topics (**FSP2**)	"La siguiente es la descripcion de un convenio interadministrativo entre dos entidades publicas en Colombia. Usando tu conocimiento sobre politicas publicas, el contexto juridico y administrativo colombiano y la descripcion del contrato, tu tarea es decidir si el contrato hace referencia al ambito ambiental. Por ambito ambiental me refiero a todos los temas relacionados con la gestion ambiental (como la protección y gestion de recursos naturales y biodiversidad) y tambien a temas cercanos, especificamente aquellos relacionados con: mineria, energia, agricultura, desarrollo sostenible, agua potable y disposicion de residuos, calidad del aire, cambio climatico, gestion de	"The following is a description of an inter-administrative agreement between two public entities in Colombia. Using your knowledge of public policies, the Colombian legal and administrative context, and the contract description, your task is to decide whether the contract refers to the environmental field. By environmental field, I mean all issues related to environmental management (such as the protection and management of natural resources and biodiversity) and also related topics, specifically those related to mining, energy, agriculture, sustainable development, drinking water and waste disposal, air quality, climate change, risk and disaster management associated with natural phenomena, and land use

	riesgos y desastres asociados a fenomenos naturales y uso del suelo asociado a la conservacion. Responde 1 si el contrato se refiere a alguno de estos temas y 0 si no lo hace. Solo responde 1 o 0 y no introduzcas ni justifiques ni expliques tu respuesta"	associated with conservation. Answer 1 if the contract refers to any of these issues and 0 if it does not. Answer only 1 or 0 and do not introduce, justify, or explain your answer."
Few-shot, description of what is and is not environment-related (**FPS3**)	"La siguiente es la descripcion de un convenio interadministrativo entre dos entidades publicas en Colombia. Usando tu conocimiento sobre politicas publicas, el contexto juridico y administrativo colombiano y la descripcion del contrato, tu tarea es decidir si el contrato hace referencia al ambito ambiental. Por ambito ambiental me refiero a todos los temas relacionados con la gestion ambiental (como la protección y gestion de recursos naturales y biodiversidad, gestions de recursos hidircos) y tambien a los temas cercanos, especificamente aquellos relacionados con: mineria, energia, agricultura, desarrollo sostenible, agua potable y disposicion de residuos, calidad del aire, cambio climatico, gestion de riesgos y desastres asociados a fenomenos naturales, y uso del suelo asociado a la conservacion. Responde 1 si el contrato se refiere a alguno de estos temas y 0 si no lo hace. Por ejemplo, los convenios relacionados con los siguientes temas no lo hacen y reciben un 0: saneamiento de titulos, salud publica, temas deportivos, de pobreza y desarrollo que no esten directamente viculados con el agro, infraestructura que no este especificamente relacionada con la gestion ambiental, climatica, de aguas o residuos, o energia. Solo responde 1 o 0 y no introduzcas ni justifiques ni expliques tu respuesta"	"The following is a description of an inter-administrative agreement between two public entities in Colombia. Using your knowledge of public policies, the Colombian legal and administrative context, and the contract description, your task is to decide whether the contract refers to the environmental field. By environmental field, I mean all issues related to environmental management (such as the protection and management of natural resources and biodiversity, water resource management) and also related topics, specifically those related to: mining, energy, agriculture, sustainable development, drinking water and waste disposal, air quality, climate change, risk and disaster management associated with natural phenomena, and land use associated with conservation. Answer 1 if the contract refers to any of these topics and 0 if it does not. For example, agreements related to the following topics do not refer to these topics and receive a 0: land title regularisation, public health, sports, poverty and development issues not directly linked to agriculture, infrastructure not specifically related to environmental, climate, water or waste management, or energy. Answer only 1 or 0 and do not introduce, justify, or explain your answer."
Few-shot, description of environmental topics and examples from the dataset (**FPS4**)	"La siguiente es la descripcion de un convenio interadministrativo entre dos entidades publicas en Colombia. Usando tu conocimiento sobre politicas publicas, el contexto juridico y administrativo colombiano y la descripcion del contrato, tu tarea es decidir si el contrato hace referencia al ambito ambiental. Por ambito ambiental me refiero a todos los temas relacionados con la gestion ambiental (como la protección y gestion de recursos naturales y biodiversidad, gestions de recursos hidircos) y tambien a los temas cercanos, especificamente aquellos relacionados con: mineria, energia, agricultura, desarrollo sostenible, agua potable y disposicion de residuos, calidad del aire, cambio climatico, gestion de riesgos y desastres asociados a fenomenos naturales, y uso del suelo asociado a la conservacion. Responde 1 si el contrato se refiere a alguno de estos temas. Los siguientes son ejemplos de descripciones de convenios que SI se refieren a estos temas: 'promover el mejoramiento de los recursos naturales a traves de acciones ambientales mediante la metodologia priser en la vereda tocaima del municipio de alejandria'; 'elaborar estudios de detalle y disenos de obras de mitigacion para la reduccion del riesgo por inundaciones y avenidas torrenciales en la vereda la villa sectores villa esperanza y villa triunfo ubicados en el area rural del municipio de san carlos'; 'aunar esfuerzos tecnicos administrativos y financieros para fortalecer las capacidades en comercializacion de comunidades indigenas y pequenos productores de maiz mediante el apoyo a las actividades agroalimentarias a traves de la entrega de semilla mejorada	"The following is a description of an inter-administrative agreement between two public entities in Colombia. Using your knowledge of public policies, the Colombian legal and administrative context, and the contract description, your task is to decide whether the contract refers to the environmental field. By environmental field, I mean all issues related to environmental management (such as the protection and management of natural resources and biodiversity, water resource management) and also related topics, specifically those related to: mining, energy, agriculture, sustainable development, drinking water and waste disposal, air quality, climate change, risk management and disasters associated with natural phenomena, and land use associated with conservation. Answer 1 if the contract refers to any of these topics. The following are examples of descriptions of agreements that DO refer to these topics: 'Promote the improvement of natural resources through environmental actions using the PRISER methodology in the Tocaima district of the municipality of Alejandría'; 'Prepare detailed studies and designs for mitigation works to reduce the risk of flooding and torrential floods in the La Villa district, Villa Esperanza and Villa Triunfo sectors, located in the rural area of the municipality of San Carlos'; 'to combine technical, administrative, and financial efforts to strengthen the marketing capacities of indigenous communities and small-scale maize producers by supporting agri-food activities through the provision of certified improved maize seed, inputs, training, and support.' If the agreement does not refer to the aforementioned and exemplified topics, the response is 0. For example, agreements related to the following topics do not meet the

certificada de maiz insumos capacitacion y acompanamiento.' Si el convenio no se refiere a estos temas mencionados y ejemplificados, responde 0. Por ejemplo, los convenios relacionados con los siguientes temas no cumplen con las condiciones para ser carecterizados como ambientales y reciben un 0: saneamiento de titulos, salud publica, temas deportivos, de pobreza y desarrollo que no esten directamente viculados con el agro, infraestructura que no este especificamente relacionada con la gestion ambiental, climatica, de aguas o residuos, o energia. Los siguientes son ejemplos de descripciones de convenios que NO pertenecen a la categoria de temas ambientales como se definio mas arriba y por tanto recibirian 0: 'aunar esfuerzos tecnicos administrativos y financieros para el mejoramiento de la via terciaria que comunica la vereda pueblo viejocon la vereda penas blancas sector el volador en el municipio de cabrera cundinamarca'; 'aunar esfuerzo tecnicos administrativos financieros y juridicos con el municipio de el playon para la conformacion y cofinanciacion de bolsa comun de recursos del programa de alimentacion escolar pae en el departamento de santander para la vigencia 2023'; 'prestar colaboracion armonica entre la superintendencia de notariado y registro y el municipio de sabanalarga brindando apoyo humano tecnico y logistico con el fin de obtener la titulacion saneamiento y formalizacion de la propiedad inmobiliaria urbana en el municipio implementando de manera conjunta los procedimientos juridicos y administrativos establecidos en la normatividad vigente.' Solo responde 1 o 0 y no introduzcas ni justifiques ni expliques tu respuesta"

conditions to be characterised as environmental and receive a 0: land title regularisation, public health, sports, poverty and development issues not directly linked to agriculture, infrastructure not specifically related to environmental, climate, water, waste, or energy management. The following are examples of agreement descriptions that DO NOT fall into the environmental issues category as defined above and therefore would receive a score of 0: 'to join technical, administrative, and financial efforts to improve the tertiary road connecting the Pueblo Viejo area with the Penas Blancas area, El Volante sector, in the municipality of Cabrera, Cundinamarca'; 'to join technical, administrative, financial, and legal efforts with the municipality of El Playón to establish and co-finance a common resource pool for the PAE school feeding program in the department of Santander for the 2023 period'; 'to provide harmonious collaboration between the Superintendency of Notaries and Registry and the Municipality of Sabanalarga, providing human, technical, and logistical support to obtain the titling, sanitation, and formalization of urban real estate property in the municipality, jointly implementing the legal and administrative procedures established in current regulations.' Answer only 1 or 0 and do not introduce, justify, or explain your answer."

Each prompt was tested on two independent 100-item subsamples at two temperature settings (0.1 and 0.9), producing four runs per prompt, which also allowed me to test the stability of the prompts (Barrie et al., 2024a). Performance was assessed against the manual labels using accuracy, recall, precision, and F1 scores. Table A 2 reports the values for each run of the prompt at each temperature. The more elaborate few-shot prompts (FSP3 and FSP4) consistently outperformed simpler formulations, with slightly better results at higher temperatures.

Table A 2. Prompt engineering evaluation – Whole network (Open Mistral Nemo 24.07)

Prompt	Tempt	Run	Accuracy	Recall	Precision	F1
ZSP	0.1	1	0.87	0.775	0.735	0.752
		2	0.87	0.796	0.759	0.775
	0.9	1	0.81	0.770	0.673	0.697
		2	0.80	0.704	0.660	0.675
FSP1	0.1	1	0.63	0.755	0.623	0.571
		2	0.52	0.689	0.608	0.496
	0.9	1	0.58	0.726	0.610	0.532
		2	0.55	0.707	0.615	0.52
FSP2	0.1	1	0.91	0.768	0.830	0.794
		2	0.91	0.820	0.837	0.828
	0.9	1	0.89	0.816	0.770	0.790
		2	0.88	0.802	0.775	0.787

FSP3	0.1	1	0.92	0.834	0.834	0.834
		2	0.91	0.820	0.837	0.828
	0.9	1	0.92	0.774	0.867	0.811
		2	0.87	0.796	0.759	0.775
FSP4	0.1	1	0.91	0.679	0.953	0.738
		2	0.93	0.807	0.921	0.850
	0.9	1	0.93	0.75	0.962	0.814
		2	0.92	0.775	0.911	0.823

I then repeated the classification test using a larger model, Mistral Large 2411 (weights available here), with prompts FPS3 and FPS4 in a new subsample of 100 contracts from the manually classified dataset. This yielded further gains, with FPS4 performing best with a temperature of 0.9. Table A 3 reports the predictive metrics. I used this model and setup to classify the full dataset.

Table A 3. Prompt engineering evaluation – Whole network (Mistral Large 2411)

Prompt	Tempt	Accuracy	Recall	Precision	F1
FSP3	0.1	0.91	0.946	0.82	0.862
	0.9	0.92	0.952	0.833	0.875
FSP4	0.1	0.92	0.952	0.833	0.875
	0.9	0.94	0.964	0.864	0.903

Assessed against the full 2,000-item ground-truth set, the final prompt achieved 99.1% accuracy, 98.6% recall, 98.4% precision and an F1 of 0.985. I then manually reviewed and corrected the residual false positives and negatives.

ii. Rule-based refinements

To address systematic edge cases, I applied targeted rule-based filters. Among LLM negatives, I searched for environmental keywords and institutional cues (e.g., “acueducto,” “residuos,” “calidad del aire,” “corporación autónoma”) to recover missed contracts, especially for water and sanitation infrastructure. Among LLM positives, I excluded recurrent false positives (e.g., slaughterhouse facilities, livestock transport permits, and sports agreements). After these refinements, the final dataset consisted of 4,716 contracts, which form the basis of the environmental collaboration network analysed in the dissertation.

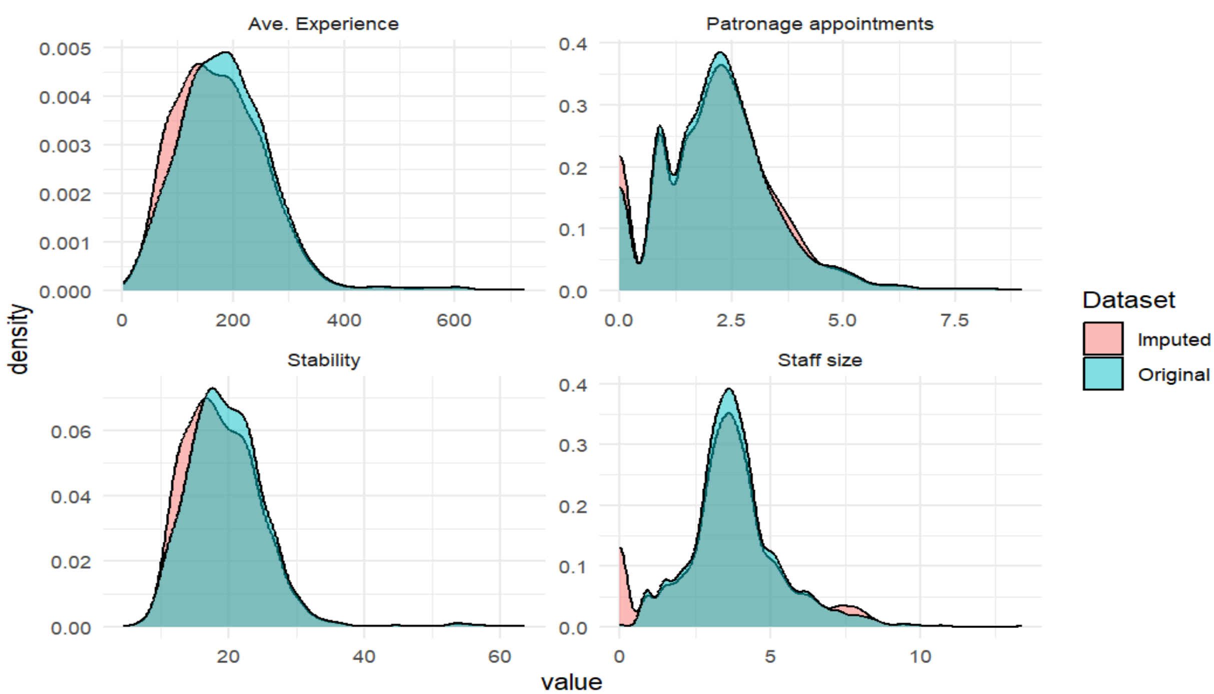
B. Appendix 2. Multiple imputation

a. Full network dataset

Some organisations lacked complete data in the official administrative sources. Out of the universe of public entities, 240 had no employment information and a further 134 had partial missingness. Among the key variables used in the analysis—staff size, rank, and experience—missingness ranged between 10% and 18%. To retain these agencies in the analysis, I employed multiple imputation using denoising autoencoders, a machine learning approach to multiple imputation recently developed by Lall and Robinson (2022). This machine learning approach treats missing entries as "corrupted" data, trains a neural network to reconstruct the original dataset from partially corrupted inputs, and draws imputations from the reconstructed outputs. By learning complex nonlinear relationships and avoiding restrictive distributional assumptions, MIDAS offers advantages over conventional multiple imputation methods. I implemented the procedure in `R` with the `rMIDAS` package (Lall & Robinson, 2022), training the network for 25 epochs on the full dataset (including incomplete observations) and generating 20 multiply imputed datasets. The model converged with a final RMSE loss of 14.52, and I averaged across the 20 completed datasets to obtain the imputed values.

To assess imputation quality, I compared the distributions of observed and imputed values using Welch's t-tests, Wilcoxon rank-sum tests (for differences in medians under non-normality), and Kolmogorov–Smirnov tests (for overall distributional similarity). I also computed Cohen's *d* to gauge the magnitude of differences. Overall, imputed variables closely resembled the original ones: most tests failed to reject the null of equal distributions, and in cases where differences emerged, effect sizes were very small (none exceeded 0.1 standard deviations). Figure A 1 illustrates this by plotting the distributions of selected key variables for the observed and imputed values.

Figure A 1. Examples of imputation performance



Note: Values for number of patronage appointments and staff size are inverse sine-transformed to facilitate visualisation.

C. Appendix 3. Bureaucratic stability measure

For collaboration to be effective, a stable organisational environment is essential. Research on collaborative and network governance highlights the importance of sustained interactions for trust building, information exchange, and joint learning (Ansell & Gash, 2008; Berardo & Scholz, 2010; Emerson et al., 2012; Lubell, 2013; Provan & Milward, 2001; Bodin et al., 2017; Metz et al., 2019). Bureaucrats need time both to cultivate trust and to learn the intricate routines of collaboration. Stability is therefore closely linked to bureaucrats' tenure length and the continuity of their roles (Geys et al., 2023).

A limitation of the employment data used here is that they are cross-sectional: I only observe the date each employee began their current post, not whether or when they exit. To address this, I construct a proxy for organisational stability based on employees' expected tenure. The measure leverages two key pieces of information: time already spent in the organisation and contract type (permanent, at-will, fixed-term, provisional, or elected).

First, I estimate Kaplan–Meier (K-M) survival curves stratified by contract type. K-M curves model the probability that an employee remains in the organisation beyond a given tenure length (usually applied in medical sciences to test the probability that a patient survives a given time after a disease or treatment, see Dudley et al., 2016). The advantage of K–M estimation is that it handles right-censored data (Satten & Datta, 2001). For estimation, I follow an approach similar to Box-Steffensmeier et al. (2015) and treat all employees as right-censored at the date of data collection—that is, those still employed are assumed to have tenure censored at that point. While this is a strong assumption, it provides a systematic way to use the observed entry dates to estimate tenure distributions. In practice, this means the curves capture the expected tenure conditional on observed entry.

Formally, let T denote the random variable representing the tenure length of an employee. The probability that tenure exceeds time *t* is defined by the survival function

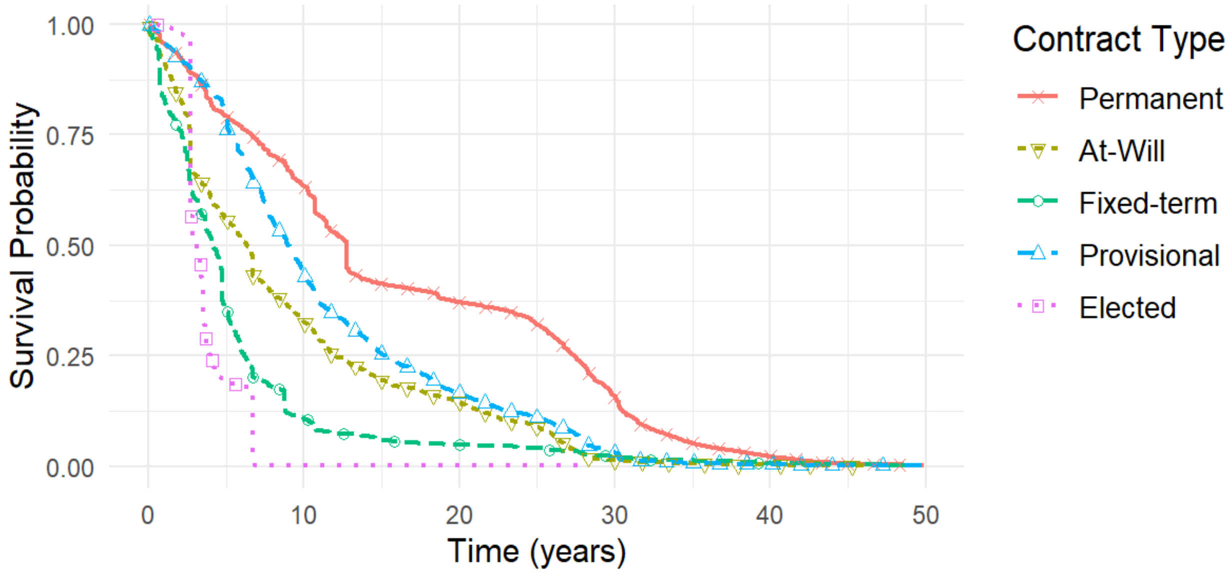
$$S(t) = \Pr(T > t) \tag{5}$$

The K-M method uses non-parametric maximum likelihood to estimate this function $S(t)$. Suppose observed exit times are ordered as $t_{(1)} < t_{(2)} < \cdots < t_{(m)}$, with d_j denoting the number of exits (in this case, employees leaving) at time $t_{(j)}$, and n_j the number of individuals "at risk" just before $t_{(j)}$. The K-M estimate at time t is then given by

$$\hat{S}(t) = \prod_{t_{(j)} \leq t} \left(1 - \frac{d_j}{n_j}\right) \tag{6}$$

This is a stepwise function that decreases at each observed exit time and remains constant between events. Figure A 2 presents the K-M survival curves of public employees in my dataset stratified by contract type. A log-rank test confirms that survival distributions differ significantly across contract types, with permanent staff clearly displaying longer tenures, which makes this category a good predictor of tenure length.

Figure A 2. Kaplan-Meier survival curves by contract type

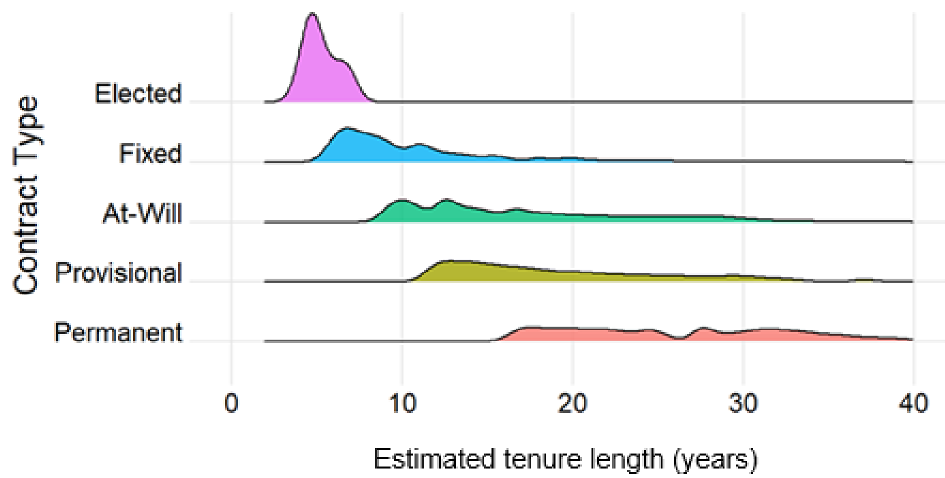


Second, I use these estimated survival functions to calculate the expected remaining tenure for each employee. Specifically, as I observe each employee's current tenure t_0, I can deduct the expected remaining tenure from the curve. This is given by the integral of the curve at given time, normalised by $S(t_0)$ to reflect the fact that the employee is known to have survived at least to that point. This can be expressed as

$$E(T - t_0 \mid T > t_0) = \frac{1}{S(t_0)} \int_{t_0}^{\infty} S(u)du \tag{7}$$

To obtain the total expected tenure, I then add this expected remaining time to the individual's observed tenure. This approach yields an estimate of the overall length of tenure each employee is expected to complete, conditional on their contract type and current tenure. I compute this for each employee and then aggregate at the organisational level by taking the mean expected tenure across staff. The resulting measure captures the average stability of the workforce. As a plausibility check, the final expected tenure for elected officials—whose term limit is four years—centres around 5.2 years (SD = 1.2, median 4.8), a close approximation given the right-censoring assumption. While the measure slightly overestimates absolute tenure, it provides a consistent and comparable proxy for bureaucratic stability across organisations, with higher values indicating lower churn and greater continuity.

Figure A 3. Estimated tenure length by contract type



D. Appendix 4. Summary statistics

Table A 4. Summary of main continuous covariates

Variable	Mean	Median	SD	Min	Max
Overall patronage: % of staff politically appointed	0.31	0.24	0.26	0.00	1.00
Managerial patronage: % of managerial staff politically appointed	0.75	0.80	0.29	0.00	1.00
Professional patronage: % of mid-rank professional staff politically appointed	0.18	0.00	0.32	0.00	1.00
No. of employees	114.27	19.00	773.20	1.00	24,745.00
Bureaucratic stability: Average expected tenure length (in years)	18.38	17.70	5.40	4.56	57.43
Technical capacity (% staff with postgraduate degree)	0.25	0.21	0.20	0.00	1.00
Average experience in the public sector (in months)	165.02	155.79	78.83	3.78	622.23
No. of people affected by climate events in jurisdiction	1,364.61	252.00	3,698.78	0.00	34,852.00
Geographical distance between collaborators (in km)	117.80	52.15	177.65	0.00	1,256.64

Table A 5. Summary of organisations' characteristics

Variable	Level	N	Share
Category of jurisdiction	ESP	227	0.13
	1	151	0.08
	2	85	0.05
	3	69	0.04
	4	60	0.03
	5	60	0.03
	6	1,152	0.64
Departamento	Antioquia	235	0.13
	Cundinamarca	171	0.09
	Boyacá	149	0.08
	Bogotá	125	0.07
	Santander	125	0.07
	Nariño	84	0.05
	Valle del Cauca	80	0.04
	Tolima	70	0.04
	Norte de Santander	59	0.03
	Bolívar	57	0.03
	Huila	55	0.03
	Cauca	51	0.03
	Caldas	49	0.03
	Meta	48	0.03
	Cesar	46	0.03
	Risaralda	46	0.03
	Córdoba	40	0.02
	Magdalena	40	0.02
	Atlántico	37	0.02
	Chocó	35	0.02
	Sucre	35	0.02
	Casanare	33	0.02
	Putumayo	25	0.01
	Quindío	25	0.01
	Caquetá	23	0.01
	La Guajira	19	0.01
	Arauca	14	0.01
	Guaviare	8	0.00
	Guainía	5	0.00
	Vichada	5	0.00
	Vaupés	4	0.00
	Amazonas	3	0.00
	Archipiélago de San Andrés, Providencia y Santa catalina	3	0.00
Government tier	Local	1,554	0.86
	Regional	148	0.08
	National	102	0.06
Organisation type	Municipality	1,098	0.61

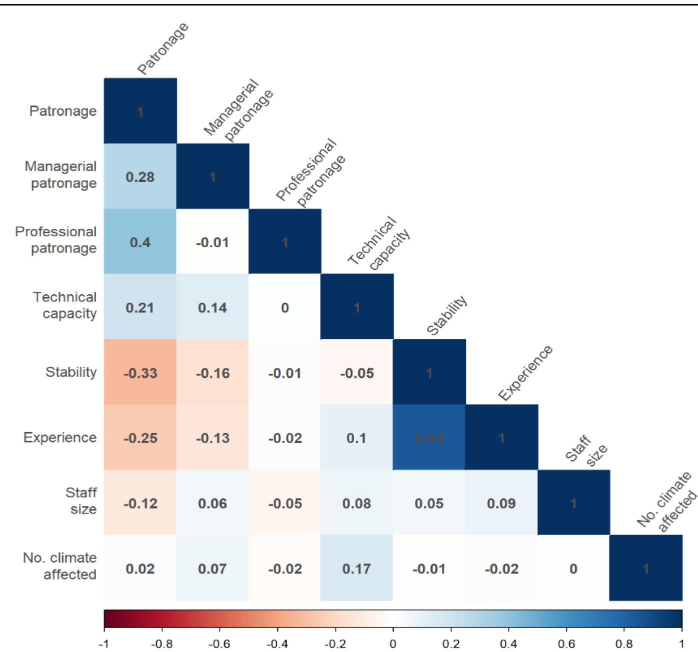
Table A 5. Summary of organisations' characteristics

Variable	Level	N	Share
	Utilities company	320	0.18
	Development agency	68	0.04
	Other	48	0.03
	University	47	0.03
	National level authority	46	0.03
	Departamento	32	0.02
	Regional environmental authority	29	0.02
	Tourism and culture agency	28	0.02
	Inter-administrative association	25	0.01
	Financial agency	18	0.01
	Health provider	17	0.01
	Scientific institute	12	0.01
	Firefighters	7	0.00
	Metropolitan authority	6	0.00
	Control and monitoring authority	3	0.00

Table A 6. Summary of homophily variables

Variable	N	Share
Agreements within the same *departamento*	1,235	0.63
Agreements within same government tier	476	0.24
Agreements same political party	499	0.26
Agreements between agencies of the same type	75	0.04

Figure A 4. Pearson correlation for main continuous variables

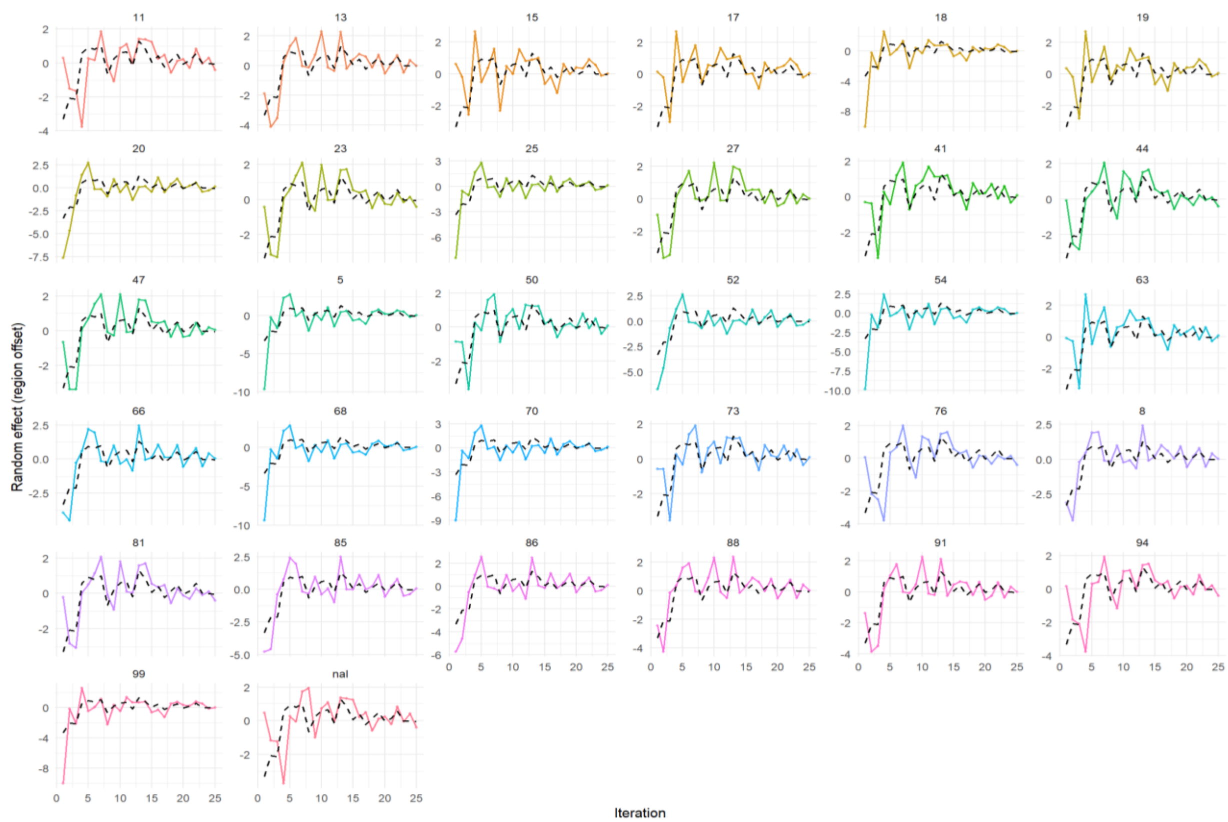


E. Appendix 5. mERGM random effects estimation, model stability and VIF

a. Random effects and structural parameters stabilisation

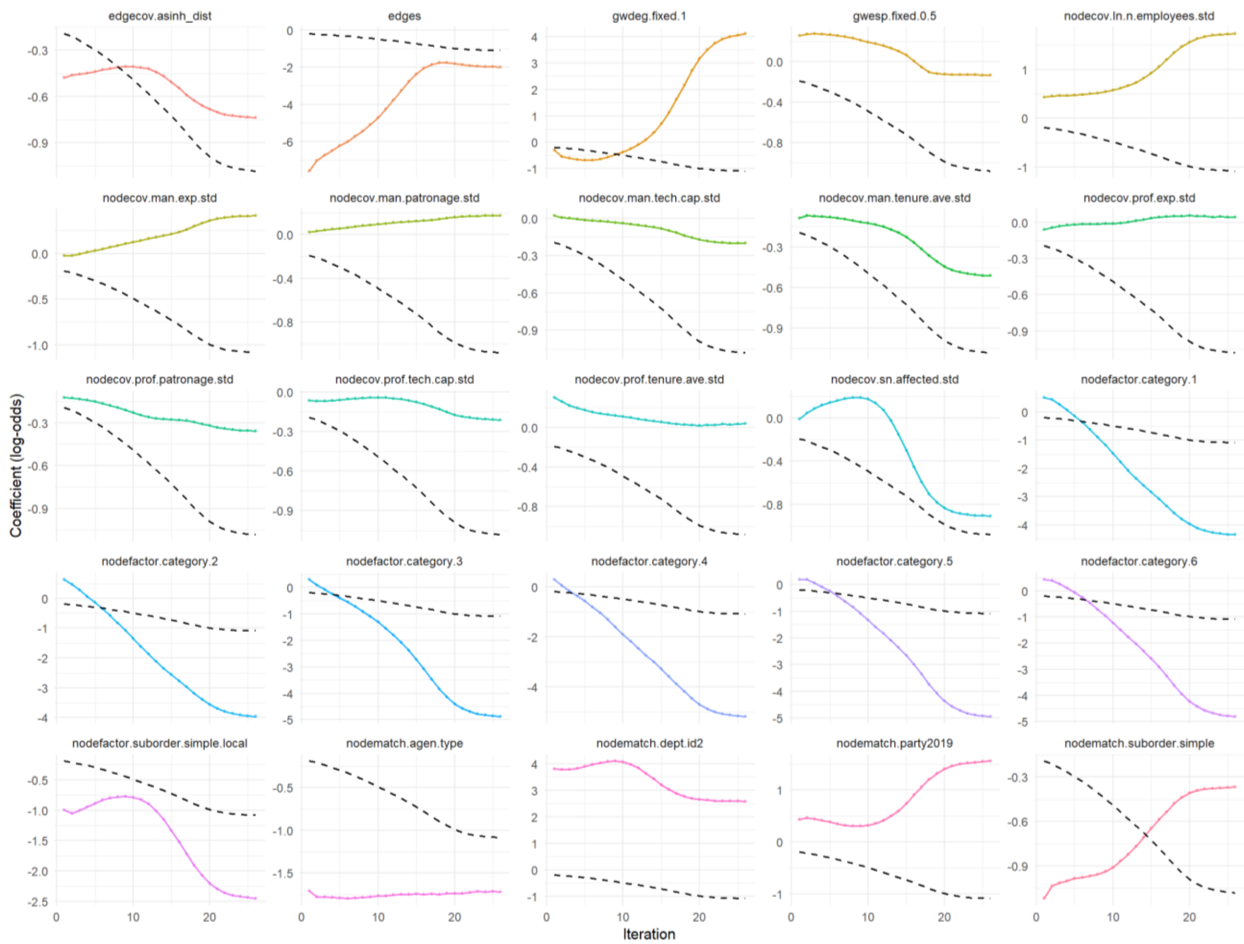
Because the mERGM is estimated iteratively alternating between ERGM updates for the structural coefficients, $\boldsymbol{\theta}$, and updates for the group random effects, $\boldsymbol{\alpha}$, though pseudolikelihood, it is important to verify that both sets of parameters have stabilised. Without stability, results could reflect noisy fluctuations rather than the underlying equilibrium of the estimation routine. To assess this, I inspect trace plots of the estimated parameters across iterations. For the random effects, stability is indicated when group-specific trajectories settle into consistent ranges rather than drifting or trending; for the structural coefficients, convergence is indicated when the traces flatten and fluctuate narrowly around a stable value. Figure A 5 and Figure A 6 present the trace plots for the random effects and structural coefficients, respectively, for model 5.

Figure A 5. Random Effects iterative estimation trace plots



Note: each plot corresponds to a departamento. Solid line shows the estimated α_g (y-axis) across each iteration (x-axis). Dashed lines represent the mean across all groups at each iteration.

Figure A 6. Structural mERGM coefficients iterative estimation trace plots



Note: each plot corresponds to a structural coefficient. Solid line shows the estimated θ (y-axis) across each iteration (x-axis). Dashed lines represent the mean across all groups at each iteration.

The stopping rule for the iterative estimation was given by $\left|\widehat{\boldsymbol{\theta}}_{(t)} - \widehat{\boldsymbol{\theta}}_{(t+1)}\right| \leq 0.05$, i.e, when the change in the structural parameters, compared to the previous interaction, was negligible. All models converged after 23 to 26 iterations. These diagnostics provide reassurance that the reported estimates represent a stable solution of the iterative algorithm rather than artifacts of premature stopping.

b. Variance Inflation Factors

Table A 7 presents the Variance Inflation Factors for the saturated model 5, lending no evidence of concerning multicollinearity.

Table A 7. Variance Inflation Factors (VIFs) for Model 5

Covariates	VIF
Managerial patronage	1.41
Managerial technical capacity	1.73
Managerial stability	2.22
Managerial public experience	2.07
Professional patronage	1.20
Professional technical capacity	1.53
Professional stability	8.93
Professional public experience	8.13
Staff size	3.75
People affected by climate-events	3.47
Government tier: Local	3.45
Geographical distance	2.18
Category 1	4.55
Category 2	3.82
Category 3	2.75
Category 4	2.61
Category 5	1.58
Category 6	6.06
Homophily: Government Tier	1.64
Homophily: Organisation Type	1.26
Homophily: Political Party	2.08
Homophily: *Departamento*	4.99
Degree distribution (GWDEG)	3.58
Transitivity (GWESP)	2.16

Note: The VIFs are calculated following the procedure proposed by Duxbury (2021). VIF values above 20 are problematic and above 100 mean severe collinearity.

F. Appendix 6. Random effects distribution and pseudo-ICC

To further underscore the value of the hierarchical approach, I present the distribution of the estimated random effects. As shown in the main results in Table 1, the standard deviation of the departamento random effects ($\sigma_{\text{Departamento}}$) is about $\sim$2.6 on the log-odds scale. This implies substantial heterogeneity agencies located in regions one standard deviation above the mean random effect have odds of collaboration roughly 13.5 times higher ($\exp(2.6) \approx 13.5$) than those in the average region. Consistent with mean shrinkage, the distribution centers on zero, but it spans from -10.1 to +2.8, indicating pronounced differences across *departamento* in their baseline propensity to collaborate.

In addition, I calculate a pseudo–intra-class correlation (pseudo-ICC) coefficient to quantify the share of residual variance in tie formation attributable to between-*departamento* differences. This statistic partitions the variance of the linear predictor into between- and within- *departamento* components, based on the estimated variance of the random effects. It is calculated as follows

$$\text{pseudoICC} = \frac{\hat{\tau}^2}{\hat{\tau}^2 + \widehat{Var}\left(X\hat{\theta}\right) + \frac{\pi^2}{3}} \tag{8}$$

Where $\hat{\tau}^2$ is the across-region variance of the estimated random effects, $\widehat{Var}\left(X\hat{\theta}\right)$ is the weighted variance of the structural linear prediction across the MPLE dyad types, and $\pi^2/3$ is the standard logistic residual variance. The resulting pseudo-ICC can be interpreted as the proportion of unexplained variation in tie formation that is attributable to clustering by departamento. While not a "true" ICC in the continuous-outcome sense (because collaboration is binary and modeled via a logistic link), the pseudo-ICC provides an interpretable summary of clustering. In this case, most models yield a pseudo-ICC of about 0.21, indicating that roughly 21% of the unexplained variation in collaboration is attributable to the departamento context beyond the observed covariates.

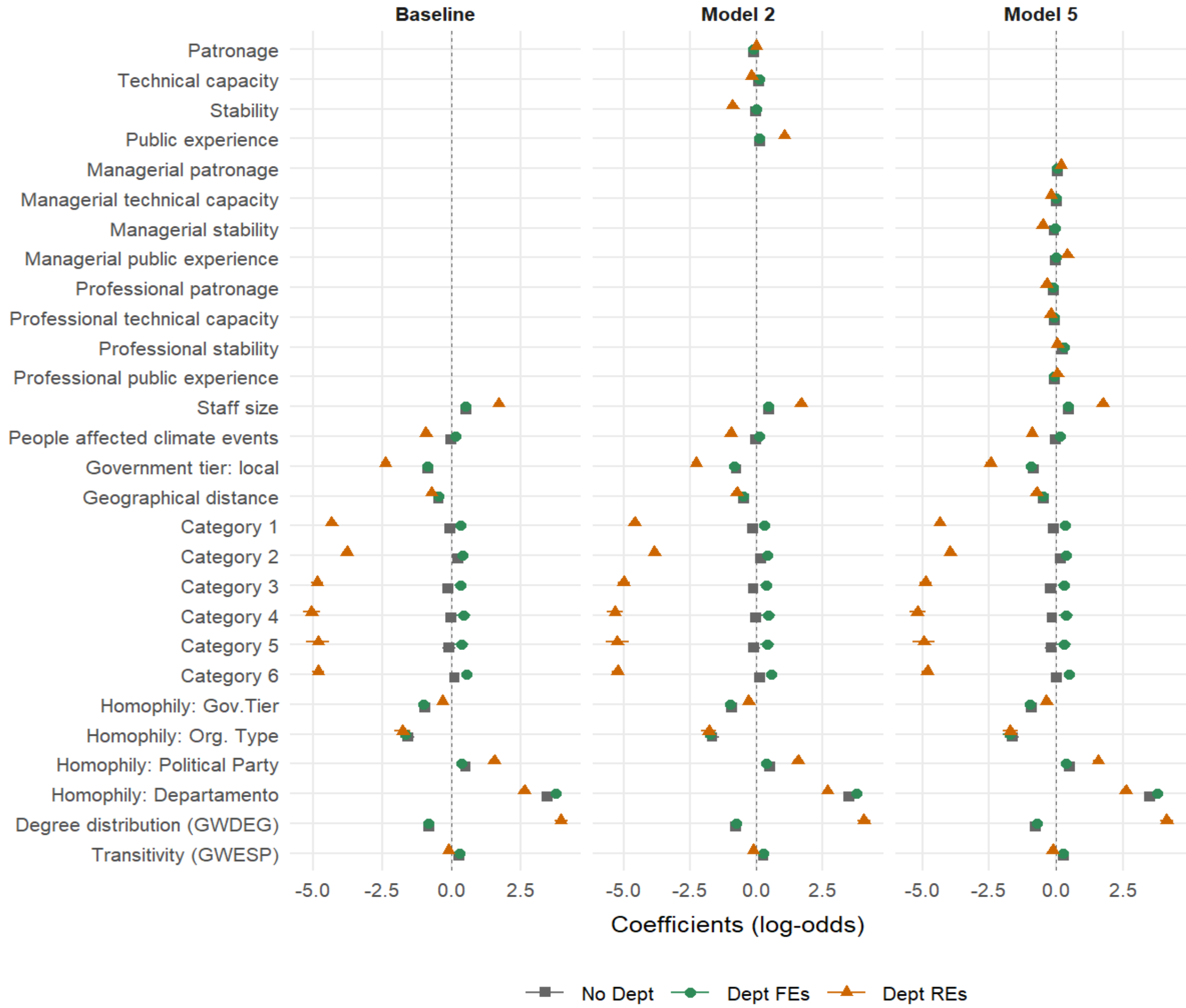
G. Appendix 7. mERGM vs ERGM comparison and model selection

a. Results comparison

In this section, I compare the results and model fit statistics of the mixed ERGMs with departamento random effects (REs) to those of standard ERGMs estimated with departamento included as a fixed effect (FEs) via the nodematch() term. For reference, I also present results from an ERGM specification that excludes the departamento variable altogether. Figure A 7 reports results for the baseline model, the specification including aggregate patronage and bureaucratic measures (Model 2), and the specification disaggregating these measures by bureaucratic rank (Model 5).

As the comparison shows, while some covariates, such as geographical distance and organisational type homophily, display similar effects across specifications, most results differ meaningfully between the FEs and REs models. Crucially, the main variables of interest—patronage and bureaucratic attributes—largely lose statistical significance in the FEs specification. For other covariates, such as staff size and political homophily, the direction of the effect is preserved, but magnitudes shrink substantially under FEs. In addition, some coefficients change sign, including the proxy for local development (category) and the number of people affected by climate events. Most strikingly, the coefficient for GWDEG, the term capturing degree distribution, reverses direction: it is large and positive in the REs models, consistent with preferential attachment and a highly centralised network structure, but negative under FEs, implying instead an egalitarian tendency against hub formation. Substantively, the REs results align more closely with the discussed institutional and administrative Colombian context, where collaborative ties are concentrated in a few highly connected agencies.

Figure A 7. mERGMs vs ERGM results



Note: The graph presents the coefficients (log-odds scale) for the models specified with *departamentos* as fixed effects (circle) and as random effects (triangle). A model with no term for departamento (square) is also added for reference.

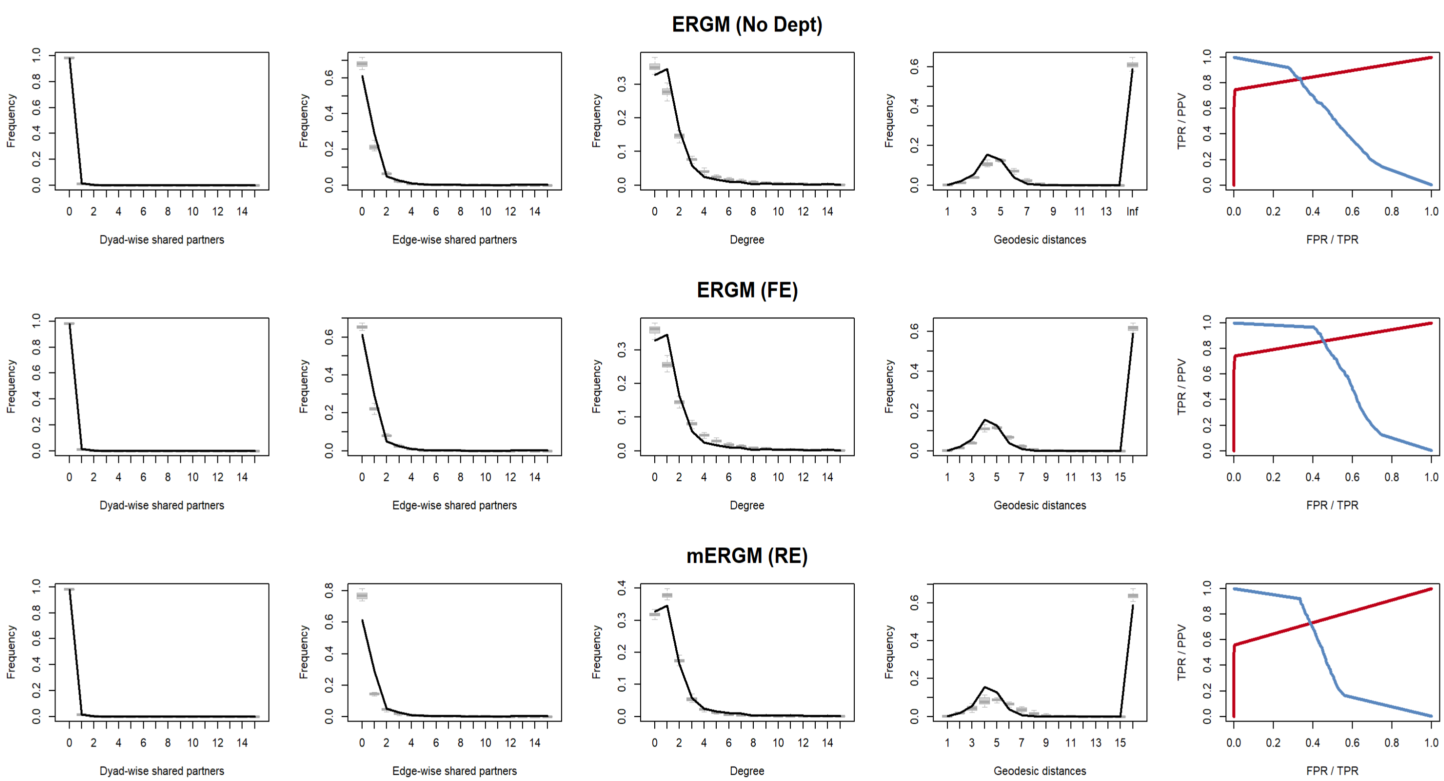
The divergence can be understood in terms of how FEs and REs handle unobserved heterogeneity across *departamentos*, particularly given the unequal distribution of agencies. Some *departamentos* host many organisations (e.g., Antioquia, with 235 organisation), while others contain only a handful (e.g., Risaralda, with 46 organisation, or La Guajira, with 19), many of which are isolates. In FEs models, each *departamento* is forced to "stand alone": all between-*departamento* variation is absorbed into its intercept, so estimates rely only on within-*departamento* variation. In sparsely populated *departamentos*, this leaves very little effective information, leading to unstable or attenuated coefficients and misestimation of structural terms such as GWDEG. Hierarchical models like the mERGM, by contrast, introduce partial pooling: *departamento*-specific propensities are modelled as draws from a common distribution, allowing *departamentos* with little information to "borrow" strength from those with more (Snijders, 2016). This reduces idiosyncratic noise while preserving systematic variation, producing more stable estimates of both covariates and structural dependencies.

From a substantive perspective, this distinction matters. The FEs specification implicitly assumes *departamentos* operate in isolation, which is implausible given the shared institutional framework of Colombian environmental governance. The REs specification, by contrast, treats *departamentos* as related but not identical, reflecting more accurately the interplay of national rules and local variation. The REs results therefore capture both the centralised tendencies of the system—evident, for instance, in the positive GWDEG effect—and the systematic correlates of collaboration across the country. In this sense, the apparent attenuation or instability of effects in the FEs models is less evidence against the theoretical mechanisms, and more a consequence of how FEs discard cross-*departamento* information, especially in smaller regions.

b. Model selection: Goodness-of-Fit statistics and AIC

Figure A 8 presents the Goodness-of-Fit (GOF) statistics for three specifications of Model 5 in Table 1: the top row presents the model without inclusion of the *departamento* covariate; middle row presents the model with *departamento* fixed effects, and the bottom row presents the mERGM with *departamento* random effects.

Figure A 8. Goodness-of-Fit Statistics across specifications (Model 5)



Note: GOF statistics are calculated using 100 simulations from each one of the fitted models. Apart from differences in *departamento* effects, all specifications use the terms in Model 5 in Table 1 in the main text. GOFs are calculated using the **btergm** package (Leifeld et al., 2018)

Goodness-of-Fit statistics compare the observed network (dark solid line) to 100 networks simulated from each fitted model (grey boxplots) along key dimensions, including the number of dyad-wise and edge-wise shared partners, the degree distribution, geodesic distances, as well as Receiver-operating curves (rightmost graphs) which show the accuracy of tie prediction. In general, all specifications produce networks relatively consistent with the patterns of the observed one, which implies that the modelling choices are appropriate for representing the observed network. Having models with different results but similar GOF statistics is not unusual. This is so because ERGM terms can capture overlapping aspects of network dependence, so they can "trade off" against each other: coefficients shift in response to the presence or absence of correlated terms, but the overall model fit remains largely unchanged. Although there are theoretical reasons to prefer the hierarchical approach, the GOF comparison does not offer conclusive evidence.

To further support model selection, I compare the Akaike Information Criterion (AIC) across specifications. A complication arises because the departamento-level random effects in the mERGM are included as offset terms, not estimated directly within the ERGM likelihood. As a result, the reference AIC produced by the **`ergm`** package is misleading because it counts each offset as if it were a fixed parameter, thereby inflating the penalty without reflecting the fact that the random effects are shrunken toward the mean and partially pooled across groups. Consequently, raw AIC values from mERGMs are not directly comparable to standard ERGM specifications. To address this, I adjust the AIC following the same general strategy used for ERGMs: simulating networks under the fitted model and approximating the log-likelihood via importance-sampling of sufficient statistics. To account for the additional complexity introduced by the random effects, I apply a penalty equal to their effective degrees of freedom, estimated in the final pseudolikelihood step. This adjustment is more conservative than treating each group effect as a fixed coefficient, because it recognises that the REs explain systematic between-region variation while still shrinking toward the overall mean.

Table A 8 reports the AIC values for three model families: models with no departamento effects, models with departamento fixed effects, and models with departamento random effects (with adjusted AIC). The model nomenclature corresponds to the specifications in Table 1 in the main text. Comparing across specifications, the adjusted AIC values show that the mERGM provides the most parsimonious account of the observed network, lending further support to the preference for the hierarchical approach.

Table A 8. AIC comparison across ERGM and mERGM specifications

Model	Baseline model	Model 2	Model 3	Model 4	Model 5
ERGM – No Dept	18288	18220	18291	18227	18209
ERGM – Dept FEs	18047	17965	18054	17949	17949
mERGM Dept REs	15614	16829	15756	15588	15427

H. Appendix 8. Interaction models

Here I present the full results for the interaction models for each of the patronage measures at the different aggregate levels. To facilitate convergence, each interaction is run separately, keeping all controls constant across specifications. Estimates across models are stable, which supports this modelling strategy.

Table A 9. Interaction models aggregate patronage

	Technical capacity	Stability	Public experience
Interactions			
Patronage × Technical capacity	0.052* (0.022)		
Patronage × Stability		0.304*** (0.015)	
Patronage × Public experience			0.042 (0.028)
Aggregate measures			
Patronage	-0.042 (0.043)	0.065* (0.032)	0.002 (0.040)
Technical capacity	-0.186*** (0.036)	-0.284*** (0.031)	-0.187*** (0.036)
Stability	-0.897*** (0.048)	-0.938*** (0.042)	-0.890*** (0.048)
Public experience	1.035*** (0.050)	1.169*** (0.046)	1.051*** (0.049)
Controls			
Staff size	1.679*** (0.030)	1.558*** (0.027)	1.680*** (0.031)
People affected by climate-events	-0.971*** (0.022)	-0.938*** (0.022)	-0.961*** (0.021)
Government tier: Local	-2.297*** (0.089)	-1.627*** (0.091)	-2.287*** (0.086)
Geographical distance	-0.742*** (0.038)	-0.691*** (0.039)	-0.739*** (0.037)
Category (base group: Special)			
Category 1	-4.579*** (0.073)	-4.478*** (0.065)	-4.601*** (0.074)
Category 2	-3.847*** (0.080)	-3.632*** (0.073)	-3.859*** (0.080)
Category 3	-5.018*** (0.116)	-4.571*** (0.119)	-4.998*** (0.113)
Category 4	-5.322*** (0.152)	-4.479*** (0.126)	-5.338*** (0.152)
Category 5	-5.222*** (0.217)	-4.529*** (0.198)	-5.229*** (0.215)
Category 6	-5.200*** (0.111)	-4.101*** (0.091)	-5.223*** (0.111)
Homophily terms			
Homophily: Government Tier	-0.308*** (0.076)	-0.476*** (0.080)	-0.305*** (0.076)
Homophily: Organisation Type	-1.798** (0.146)	-1.967*** (0.139)	-1.801*** (0.145)
Homophily: Political Party	1.554*** (0.096)	1.977*** (0.090)	1.555*** (0.095)
Homophily: *Departamento*	2.669*** (0.088)	2.311*** (0.094)	2.673*** (0.086)
Endogenous terms			
Degree distribution (GWDEG)	4.026*** (0.127)	1.386*** (0.112)	4.049*** (0.124)
Transitivity (GWESP)	-0.128*** (0.026)	-0.083*** (0.024)	-0.127*** (0.025)
Edges	-1.600*** (0.160)	-0.420** (0.133)	-1.578*** (0.161)
AIC	25393	23776	25430
REs	32	32	32
$\sigma_{\text{Departamento}}$	2.7	2.74	2.74
Pseudo-ICC	0.22	0.22	0.22

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table A 10. Interaction models managerial-level patronage

	Technical capacity	Stability	Public experience
Interactions			
Man. Patronage × Man. Technical capacity	-0.055* (0.027)		
Man. Patronage × Man. Stability		0.029 (0.030)	
Man. Patronage × Man. Public experience			-0.076 (0.042)
Managerial level measures			
Man. Patronage	0.154*** (0.035)	0.177*** (0.038)	0.158*** (0.041)
Man. Technical capacity	-0.248*** (0.038)	-0.224*** (0.036)	-0.240*** (0.040)
Man. Stability	-0.513*** (0.041)	-0.494*** (0.040)	-0.517*** (0.046)
Man. Public experience	0.432*** (0.031)	0.425*** (0.032)	0.474*** (0.046)
Controls			
Professional-level patronage	-0.325*** (0.037)	-0.333*** (0.037)	-0.323*** (0.053)
Staff size	1.744*** (0.029)	1.726*** (0.028)	1.725*** (0.036)
People affected by climate-events	-0.938*** (0.022)	-0.946*** (0.022)	-0.937*** (0.032)
Government tier: Local	-2.407*** (0.083)	-2.404*** (0.082)	-2.374*** (0.107)
Geographical distance	-0.740*** (0.037)	-0.740*** (0.038)	-0.749*** (0.047)
Category (base group: Special)			
Category 1	-4.311*** (0.075)	-4.322*** (0.073)	-4.311*** (0.088)
Category 2	-3.895*** (0.078)	-3.895*** (0.082)	-3.904*** (0.081)
Category 3	-4.908*** (0.118)	-4.894*** (0.120)	-4.909*** (0.147)
Category 4	-5.130*** (0.149)	-5.118*** (0.154)	-5.102*** (0.178)
Category 5	-4.915*** (0.211)	-4.875*** (0.208)	-4.803*** (0.228)
Category 6	-4.868*** (0.108)	-4.811*** (0.108)	-4.798*** (0.136)
Homophily terms			
Homophily: Government Tier	-0.344*** (0.073)	-0.353*** (0.074)	-0.342*** (0.095)
Homophily: Organisation Type	-1.752*** (0.143)	-1.739*** (0.142)	-1.730*** (0.213)
Homophily: Political Party	1.569*** (0.094)	1.562*** (0.091)	1.592*** (0.123)
Homophily: *Departamento*	2.590*** (0.088)	2.587*** (0.085)	2.578*** (0.101)
Endogenous terms			
Degree distribution (GWDEG)	4.089*** (0.126)	4.071*** (0.127)	3.951*** (0.166)
Transitivity (GWESP)	-0.131*** (0.026)	-0.129*** (0.024)	-0.129*** (0.026)
Edges	-1.935*** (0.146)	-2.010*** (0.150)	-1.910*** (0.188)
AIC	25915	25903	25694
REs	32	32	32
$\sigma_{\text{Departamento}}$	2.62	2.62	2.62
Pseudo-ICC	0.21	0.21	0.21

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table A 11. Interaction models professional-level patronage

	Technical capacity	Stability	Public experience
Interactions			
Prof. Patronage × Prof. Technical capacity	0.064 (0.038)		
Prof. Patronage × Prof. Stability		-0.022 (0.053)	
Prof. Patronage × Prof. Public experience			-0.014 (0.039)
Professional-level measures			
Prof. Patronage	-0.360*** (0.037)	-0.353*** (0.038)	-0.356*** (0.037)
Prof. Technical capacity	-0.168*** (0.039)	-0.173*** (0.041)	-0.172*** (0.038)
Prof. Stability	-0.080 (0.072)	-0.113 (0.076)	-0.111 (0.069)
Prof. Public experience	0.113 (0.067)	0.133* (0.067)	0.131* (0.064)
Controls			
Managerial-level patronage	0.042 (0.032)	0.038 (0.033)	0.038 (0.032)
Staff size	1.706*** (0.029)	1.693*** (0.031)	1.699*** (0.031)
People affected by climate-events	-0.926*** (0.022)	-0.926*** (0.022)	-0.925*** (0.022)
Government tier: Local	-2.415*** (0.085)	-2.408*** (0.087)	-2.409*** (0.082)
Geographical distance	-0.738*** (0.037)	-0.739*** (0.036)	-0.740*** (0.038)
Category (base group: Special)			
Category 1	-4.310*** (0.075)	-4.316*** (0.075)	-4.307*** (0.072)
Category 2	-3.802*** (0.077)	-3.801*** (0.075)	-3.802*** (0.078)
Category 3	-4.760*** (0.114)	-4.763*** (0.113)	-4.770*** (0.117)
Category 4	-5.110*** (0.153)	-5.119*** (0.149)	-5.128*** (0.153)
Category 5	-4.766*** (0.210)	-4.769*** (0.223)	-4.780*** (0.211)
Category 6	-4.693*** (0.106)	-4.708*** (0.112)	-4.706*** (0.106)
Homophily terms			
Homophily: Government Tier	-0.346*** (0.074)	-0.350*** (0.073)	-0.339*** (0.074)
Homophily: Organisation Type	-1.729*** (0.143)	-1.724*** (0.148)	-1.736*** (0.146)
Homophily: Political Party	1.573*** (0.093)	1.570*** (0.094)	1.566*** (0.096)
Homophily: *Departamento*	2.595*** (0.086)	2.598*** (0.078)	2.593*** (0.085)
Endogenous terms			
Degree distribution (GWDEG)	4.040*** (0.123)	4.031*** (0.125)	4.032*** (0.125)
Transitivity (GWESP)	-0.130*** (0.024)	-0.130*** (0.025)	-0.131*** (0.024)
Edges	-2.143*** (0.140)	-2.119*** (0.144)	-2.130*** (0.147)
AIC	26187	26151	26125
REs	32	32	32
$\sigma_{\text{Departamento}}$	2.56	2.56	2.56
Pseudo-ICC	0.21	0.21	0.21

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table A 12. Interaction models patronage × political homophily

	Aggregate patronage	Managerial-level patronage	Professional-level patronage
Interactions			
Patronage × Homophily: Political Party	-0.119 (0.065)		
Man. Patronage × Homophily: Political Party		0.420*** (0.093)	
Prof. Patronage × Homophily: Political Party			0.095 (0.070)
Aggregate measures			
Patronage	0.018 (0.042)		
Technical capacity	-0.179*** (0.034)		
Stability	-0.903*** (0.046)		
Public experience	1.050*** (0.048)		
Managerial-level measures			
Man. Patronage		-0.070* (0.036)	0.038 (0.033)
Man. Technical capacity		-0.373*** (0.037)	
Man. Stability		-0.351*** (0.043)	
Man. Public experience		0.265*** (0.037)	
Professional-level measures			
Prof. Patronage		-0.092** (0.029)	-0.374*** (0.040)
Prof. Technical capacity			-0.173*** (0.040)
Prof. Stability			-0.100 (0.069)
Prof. Public experience			0.126* (0.064)
Political homophily			
Homophily: Political Party	1.490*** (0.105)	1.703*** (0.141)	1.607*** (0.098)
Controls			
Staff size	1.673*** (0.031)	1.295*** (0.034)	1.699*** (0.031)
People affected by climate-events	-0.963*** (0.022)	-1.025*** (0.025)	-0.924*** (0.021)
Government tier: Local	-2.281*** (0.084)	-1.443*** (0.089)	-2.406*** (0.087)
Geographical distance	-0.735*** (0.039)	-0.781*** (0.048)	-0.741*** (0.036)
Category (base group: Special)			
Category 1	-4.595*** (0.072)	-3.984*** (0.103)	-4.306*** (0.073)
Category 2	-3.859*** (0.077)	-3.375*** (0.087)	-3.801*** (0.078)
Category 3	-4.997*** (0.112)	-3.800*** (0.099)	-4.762*** (0.115)
Category 4	-5.331*** (0.154)	-4.231*** (0.128)	-5.113*** (0.153)
Category 5	-5.225*** (0.212)	-3.662*** (0.186)	-4.765*** (0.209)
Category 6	-5.227*** (0.105)	-3.714*** (0.105)	-4.706*** (0.107)
Homophily terms			
Homophily: Government Tier	-0.307*** (0.077)	-0.441*** (0.103)	-0.344*** (0.073)
Homophily: Organisation Type	-1.783*** (0.148)	-2.078*** (0.165)	-1.735*** (0.140)
Homophily: *Departamento*	2.679*** (0.086)	1.842*** (0.127)	2.596*** (0.083)
Endogenous terms			

Table A 12. Interaction models patronage × political homophily

	Aggregate patronage	Managerial-level patronage	Professional-level patronage
Degree distribution (GWDEG)	4.032*** (0.126)	-0.548*** (0.125)	4.036*** (0.126)
Transitivity (GWESP)	-0.130*** (0.026)	-0.045 (0.047)	-0.129*** (0.024)
Edges	-1.573*** (0.157)	0.690*** (0.200)	-2.151*** (0.146)
AIC	24297	26262	28495
REs	32	32	32
$\sigma_{\text{Departamento}}$	2.74	2.62	2.56
Pseudo-ICC	0.22	0.21	0.21

Note: * p < 0.05; ** p < 0.01; *** p < 0.001.

Table A 13. Interaction managerial-level patronage × professional-level stability

Interactions	
Man. Patronage × Prof. Stability	0.102*** (0.029)
Professional-level measures	
Prof. Patronage	-0.351*** (0.039)
Prof. Technical capacity	-0.201*** (0.041)
Prof. Stability	0.015 (0.074)
Prof. Public experience	0.049 (0.069)
Managerial-level measures	
Man. Patronage	0.189*** (0.036)
Man. Technical capacity	-0.192*** (0.038)
Man. Stability	-0.500*** (0.043)
Man. Public experience	0.404*** (0.031)
Controls	
Staff size	1.720*** (0.032)
People affected by climate-events	-0.910*** (0.023)
Government tier: Local	-2.464*** (0.083)
Geographical distance	-0.731*** (0.037)
Category (base group: Special)	
Category 1	-4.357*** (0.078)
Category 2	-3.934*** (0.079)
Category 3	-4.861*** (0.121)
Category 4	-5.155*** (0.154)
Category 5	-4.920*** (0.222)
Category 6	-4.784*** (0.110)
Homophily terms	
Homophily: Government Tier	-0.390*** (0.082)
Homophily: Organisation Type	-1.691*** (0.149)

Table A 13. Interaction managerial-level patronage × professional-level stability

Homophily: Political Party	1.564*** (0.096)
Homophily: *Departamento*	2.595*** (0.087)
Endogenous terms	
Degree distribution (GWDEG)	4.129*** (0.129)
Transitivity (GWESP)	-0.130*** (0.023)
Edges	-2.020*** (0.152)
AIC	25915
REs	32
$\sigma_{\text{Departamento}}$	2.61
Pseudo-ICC	0.21

Note: * p < 0.05; ** p < 0.01; *** p < 0.001.

Appendix references

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