

BUREAUCRATIC NEPOTISM*

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Job Market Paper

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Abstract This paper provides the first systematic empirical examination of bureaucratic nepotism and anti-nepotism legislation in an entire modern bureaucracy. By linking confidential information on family ties and administrative employer-employee records for the universe of civil servants in Colombia, I uncover three sets of empirical findings. First, using a novel methodology of family network reconstruction, I provide evidence on the pervasiveness of close family connections in the public administration and demonstrate its negative relationship with the performance of public sector agencies. Second, by further exploiting within-bureaucrat variation in family connections generated by the turnover of top *non-elected* bureaucrats, I show that family connections to public sector managers and advisors distort the allocation and compensation of workers at lower levels of the hierarchy. Connected bureaucrats receive higher salaries and are more likely to be hierarchically promoted but are negatively selected in terms of public sector experience, education, and records of misconduct. Third, I evaluate an anti-nepotism legislation reform by exploiting a sharp discontinuity in the set of family connections restricted by this law. I prove the limited effectiveness of this reform and show how bureaucrats strategically responded to this policy change by substituting margins of favoritism and reshuffling posts within the public administration.

Keywords: Favoritism, Nepotism, Bureaucracy, Public Sector Reform, Public Sector Managers.

JEL Classification Codes: D72, D73, D85, J12, J45

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1 Introduction

Bureaucratic nepotism¹ is one of the most chronic and hard-to-identify pathologies within public administrations (World Bank, 2020; Meyer-Sahling et al., 2018). It directly affects the allocation and compensation of public sector workers, which are both critical determinants of state capacity (Finan et al., 2017; Besley et al., 2021; Xu, 2018). Although most countries have implemented civil service reforms aimed to eradicate it (Mulcahy, 2015; Grindle, 2012), the perception of favoritism by government officials in these countries remains high, and complaints about this practice within public organizations are recurring.² Identifying the actual magnitude of this phenomenon, why it has been so persistent, and what are its consequences in modern bureaucracies is fundamental for strengthening state capabilities worldwide.

As with many other forms of favoritism in the public sector, the ultimate impact of bureaucratic nepotism is theoretically ambiguous (Chandrasekhar et al., 2020; Bramoullé & Goyal, 2016; Bramoullé & Huremovic, 2018; Alger & Weibull, 2010; Prendergast & Topel, 1996). On the one hand, top bureaucrats could use their discretionary power and family networks to reduce informational frictions and screen for more qualified and motivated government employees. On the other hand, nepotistic bureaucrats could substitute competent individuals for less capable family connections with negative impacts on government effectiveness.³

Despite plenty of anecdotal accounts and qualitative evidence on this issue (Meyer-Sahling et al., 2018), we know very little about the magnitude, operation, and effects of nepotism in modern bureaucracies, especially when exercised by top *non-elected* bureaucrats such as public sector managers and supervisors. This lack of empirical evidence starkly contrasts with the extensive literature on the role of political connections (Colonnelli et al., 2020; Brassiolo et al., 2020; Iyer & Mani, 2012; Fisman, 2001), political dynasties (Dal-Bó et al., 2009; Querubin, 2016; Dal Bó et al., 2017; George, 2020), and family connections to politicians in determining private and public employment outcomes (Fafchamps & Labonne, 2017; Folke et al., 2017; Gagliarducci & Manacorda, 2020; Cruz et al., 2017).⁴ The study of nepotism in bureaucracies has proven challenging due to the lack of comprehensive data on family connections, performance, and career paths of workers *within* the public sector.

¹Throughout the paper I follow the standard definition of nepotism as "the showing of special favor or unfair preference to a relative in conferring a position or a job (Oxford, 2021)". However, I focus on this favoritism when exercised by public sector managers and other top *non-elected* bureaucrats instead of by politicians. I refer to this specific form of favoritism as Bureaucratic Nepotism to distinguish it from political patronage and dynastic politics.

²See, Appendix Tables A-1 and A-2 for a cross-country tabulation of the incidence of anti-nepotism legislation and the perception of favoritism by government officials around the world. For recent reports on nepotism in the public sector see, for example, [https://news.google.com/search?q=\(nepotism\)OR\(nepotismo\)AND\(public*\)](https://news.google.com/search?q=(nepotism)OR(nepotismo)AND(public*)).

³Theoretical arguments against the presence of family connections within the public sector, in general, and against kin favoritism, in particular, trace back to the seminal works of Weber (1922). Cross-country evidence seems to validate the theoretical concern that allowing such connections could lead to non-meritocratic appointments and poor government effectiveness. See, for example, Appendix Figure A-1 and Evans and Rauch (1999); Cornell et al. (2020).

⁴As Besley et al. (2021) have recently pointed out, this distinction between bureaucrats and politicians is key to understanding the organizational economics of the state. Bureaucrats not only face different incentives and job security once in office but are also accountable to a different set of principals (Alesina & Tabellini, 2007, 2008; Spenkuch, Teso, & Xu, 2021).

In this paper, I contribute to our understanding of bureaucratic nepotism by studying its extent, functioning, and consequences within an *entire* public administration. The empirical analysis focuses on Colombia and the role that public sector managers and advisors had in allocating and compensating middle- and lower-tier workers from 2011 to 2017. Colombia provides an ideal laboratory to study this phenomenon because despite having a career civil service system since 1991 — where qualifications and seniority determine pay raises and promotions — public sector managers and advisors still retain a lot of discretion in determining public employment outcomes.⁵

Bureaucratic nepotism is extremely challenging to detect. Ideally, one needs to observe not only family connections between public sector workers but also their whole career progression within the public administration. The latter must specify exactly when hirings, promotions, and pay raises occur since the manifestation of this form of favoritism is inherently dependent on the timing of the events. For example, the mere presence of two family members in the same institution does not directly prove the existence of nepotistic practices. People may find romantic partners in the workplace or select into the same institutions for a variety of reasons. Additionally, to identify nepotism econometrically, one requires variation in family connections that is arguably exogenous to the evolution of employment outcomes. Finally, since one of the ultimate goals of studying nepotism from an economics perspective is to assess its potential distortive effects, one also needs to observe meaningful and comparable measures of performance to evaluate its implications for public sector outcomes and citizens' welfare.

To overcome these empirical challenges, I leverage fine-grained administrative data tracing the *universe*⁶ of civil servants in Colombia over seven years.⁷ I collect and combine detailed biographical information from CVs, employer-employee records, and the mandatory but confidential disclosure of family ties — in the first degree of consanguinity and affinity⁸ — of every worker in the public administration. This extensive data collection effort allows me to reconstruct the full career paths of 1,083,714 public servants and their extended family networks, linking more than 2,400,000 individuals via predetermined consanguinity and affinity ties.⁹ I complement this information with agency-specific indices of institutional performance and information on the historical and contemporaneous presence of misconduct at the individual level.¹⁰

I use two sources of identifying variation in the empirical strategy. First, I leverage

⁵As found in many other developing countries, public sector managers oversee task assignments, promote and recommend bureaucrats to leadership positions, and intervene in selecting temporary contractors (IDB, 2014).

⁶My analysis only excludes politicians, the police and military forces.

⁷More specifically, from 2011 to 2017. Even though I can trace workers since the entry into the labor force, my data on earnings limits my analysis to observations from 2011 onward.

⁸These degrees correspond to reporting parents, children, and spouse. To guide the reader Figure A-2 presents the mapping between degrees of consanguinity and family relationships.

⁹Remarkably, all these datasets are completely de-anonymized and updated annually. They contain comprehensive information on CVs, full names, sex, and national identification numbers that allow me to perfectly identify family connections and career progress within the public administration.

¹⁰These records include the presence of disciplinary, criminal, and fiscal investigations and sanctions with all the potential inabilities that such records generate for the employment of these workers in the future.

the timing of top bureaucrat turnovers to evaluate how changes in family connections to public sector managers and advisors impact the allocation and compensation of public sector workers. Second, I exploit a sharp discontinuity in the 2015 anti-nepotism legislation reform in Colombia that prohibited the appointment, nomination, and contract of relatives up to four degrees of consanguinity within public sector organizations. Both sources of variation allow me to study the ultimate impact of family connections to top bureaucrats before and after enforcing a more comprehensive anti-nepotism legislation.

The empirical analysis proceeds in three steps. In the first part of the paper, I document four new empirical facts about family connections in the public administration. First, I show that 26% of family connections recovered by my network reconstruction algorithm come precisely from connections in the first degree of consanguinity and affinity between family members who are, or eventually become, public servants between 2011 and 2017. Second, I show that family connections are pervasive. I find that around 38% of workers have a relative in the public administration, 18% have a family connection to a top bureaucrat, while around 11% work with a family member in the same agency. Third, I find that when family connections occur, they happen among close family members. I show that the average consanguinity degree between bureaucrats across families is about 2.61, with a highly concentrated distribution below four degrees of consanguinity. Finally, using data on agency-specific indices of institutional performance, I show that a one standard deviation increase in the number of close family connections is robustly associated with a decrease of 0.24 standard deviations in agencies' overall performance.

In the second part of the paper, I quantify the nepotistic returns of family ties to top *non-elected* bureaucrats. Using within-bureaucrat variation in family connections generated by the turnover of these influential bureaucrats, I show that, on average, a public sector worker is 40% more likely to be hierarchically promoted — compared to the sample mean — and receives a 2% to 5% increase in salary when becoming family-connected to a top manager or advisor. I show that these returns materialize by benefiting connected workers within the same institution where top bureaucrats are working, rather than by the allocation of family members across higher-paid agencies. Moreover, these effects are concentrated among family connections between two to five degrees of consanguinity (e.g, brothers, uncles and cousins) rather than among parents, children, or spouses of top bureaucrats who are audited by human resources within each institution.

Moreover, I argue that these effects are most likely driven by the allocation of family members to higher remunerated contracts, the temporary promotion of workers to leadership positions, and through the temporary filling of vacancies that were in the process of being assigned via meritocratic examinations.¹¹ Consistent with these mechanisms, I show that the prospects of connected bureaucrats are closely linked to the fate of their relatives as top bureaucrats. Following the exit of managers and advisors, previously connected bureaucrats

¹¹This refers to *encargos* and *plantas provisionales*.

experience a significant reduction in total earnings and in the likelihood of being promoted, offsetting the effects of having ever won a family connection to a top bureaucrat in the past.¹²

Next, I examine the consequences of this favoritism on the type of workforce that is promoted. Building on [Voth and Xu \(2021\)](#) and [Benson et al. \(2019\)](#), I evaluate the decision process that top bureaucrats face every period when deciding whom to promote. I calculate the differences in bureaucrats' pre-promotion characteristics between promoted and passed-over workers and their relationship with family connectedness to top bureaucrats. I show that managers promote better qualified individuals in general but also that they likely to overlook these qualifications when promoting their family members. On average, promoted workers tend to have more education, more public sector experience, and fewer records of misconduct. However, those differences either disappear or completely reverse when promotees are family-connected to top bureaucrats. Therefore, this distortion is consistent with the pure extraction of private rents instead of better screening of workers via family networks. These results are based on the reconstruction of choice-sets of candidates, which allows me to restrict the comparisons only among workers within the same public sector agency, choice period, hierarchical position, and seniority level.

In the final part of the paper, I evaluate the anti-nepotism legislation reform of 2015 in Colombia (Art 2. Act 02 of 2015). Using a difference-in-differences identification strategy and exploiting a sharp discontinuity in the family ties restricted by the reform, I examine the degree to which the enforcement of a more stringent reform could effectively stop the spread of kin favoritism.

Although the reform reduced the number of illegal connections by almost 15%, it did not improve the quality of the workforce or stop kin favoritism from occurring. In fact, 40% of middle-tier and low-tier bureaucrats who were part of illegal connections a period before the reform were entirely unresponsive to the reform and 30% did not leave the public administration but simply reshuffled across public sector agencies. In addition, those who initially complied with the law, leaving the public sector, returned to become part of nepotistic networks later on, with a recidivism rate of 10% every six months.

Crucially, when looking at the reasons behind the low effectiveness of the policy change, I find that top bureaucrats strategically responded to this reform by substituting margins of favoritism. Estimated returns to hierarchical promotions decreased almost by half post 2015, while benefits through salary raises doubled during the same period. Both results are consistent with top bureaucrats changing the margins of influence from hierarchical promotions to pay raises that were not contemplated in the anti-nepotism legislation of 2015.

Taken together, these findings provide the first systematic empirical examination of

¹²Crucially, all these results address the concerns recently raised by the applied econometrics literature on the use of two-way fixed effect regressions in the presence of treatment heterogeneity and for the correct estimation of average treatment effects when using staggered and non-staggered designs ([de Chaisemartin & D'Haultfoeulle, 2020](#); [Sun & Abraham, 2020](#); [Goodman-Bacon, 2021](#)).

bureaucratic nepotism and anti-nepotism legislation in an entire modern bureaucracy. In doing so, this paper relates and contributes to multiple strands of the political economy and development economics literature.

The paper speaks to the literature on the personnel economics of the state and the importance of well-functioning bureaucracies for economic development (Finan et al., 2017; Besley et al., 2021). This literature has studied the role of pecuniary and non-pecuniary incentives for the selection, allocation, and performance of public sector workers and their ultimate impact on state capacity (Dal Bo et al., 2013; Ashraf et al., 2014, 2018; Akhtari et al., 2021; Colonnelli et al., 2020; Xu, 2018; Xu et al., 2020; Bandiera et al., 2017; Deserrano et al., 2021). The paper contributes to this literature by providing systematic empirical evidence on bureaucratic nepotism, showing its effects on the allocation and compensation of public sector workers, the quality of the selected workforce, and its relationship with public sector performance.

To the best of my knowledge, there is no other empirical study of nepotism exercised by public sector managers that 1) covers the *universe* of public sector workers and 2) that does *not* rely on proxies of family connections to determine its effects.¹³ In contrast to closely related papers (Xu, 2018; Xu et al., 2020; Brassiolo et al., 2021; Durante et al., 2011), my family network reconstruction relies on administrative data and national identification numbers to perfectly identify family linkages between workers – at all levels of the hierarchy – in a modern bureaucracy. Crucially, this measure of connectedness via blood relationships is predetermined to public employment outcomes and allows me to distinguish between the intensive margin vs. the extensive margin of family relatedness using well defined consanguinity degrees.

As opposed to the literature on political patronage (Colonnelli et al., 2020; Brassiolo et al., 2020; Do et al., 2017), political dynasties (Dal-Bó et al., 2009; Dal Bó et al., 2017; George, 2020), and the role of family connections to politicians in determining the success of individuals at private and public sector institutions (Fafchamps & Labonne, 2017; Folke et al., 2017; Gagliarducci & Manacorda, 2020; Cruz et al., 2017; Iyer & Mani, 2012), this paper focuses on the understudied role of family ties to top career bureaucrats in shaping public employment outcomes. In doing so, this paper contributes to the debate of rules vs. discretion in the allocation of public sector talent (Li, 2020; Estrada, 2019; Jia et al., 2015; Tirole, 1986) and documents the negative selection effect of nepotism exercised by public sector managers. Consequently, this paper also speaks to the recent and growing literature on the importance of managers and their practices within the public sector (Fenizia, 2021; Best et al., 2017; Rasul & Rogger, 2018). More specifically, it adds to this literature by showing *how* managers' family incentives could lead to severe distortions in the allocation of workers in the public administration, especially in developing countries where family ties are

¹³The literature so far has used family proxies such as shared last names, tax codes, birthplaces, or ethnicity that tend to overestimate the actual relatedness of individuals and confound other dimensions of social connectedness with actual kinship.

strong (Cox & Fafchamps, 2007; Alesina & Giuliano, 2010, 2014) and civil service systems are weak (Meyer-Sahling et al., 2018; IDB, 2014; Grindle, 2010). This paper also contributes to the literature on the misallocation of jobs and corruption in the public sector (Olken, 2007; Olken & Pande, 2012; Brueckner & Neumark, 2014; Weaver, 2021) by quantifying a hard-to-identify illegal behavior and exposing the difficulties to eradicate it via public sector reforms due to the strategic response of bureaucrats facing those changes.

Finally, this paper relates more broadly to the literature on social incentives within organizations (Ashraf & Bandiera, 2018; Bandiera et al., 2017) and to the labor economics literature on social networks (Eliaison et al., 2021; Kramarz & Skans, 2014), job referrals (Burks et al., 2015; Schmutte, 2015), and kin favoritism (Gagliarducci & Manacorda, 2020; Pellegrino & Zingales, 2018) primarily concentrated in the study of these phenomena within private sector organizations (Bandiera et al., 2009, 2005; Wang, 2013) or specific public sector agencies (Brassiolo et al., 2021; Durante et al., 2011). My paper contributes with an empirical methodology of family network reconstruction exportable to other contexts and by studying this understudied form of favoritism across all levels of the public sector hierarchy.

The remainder of this paper is organized as follows. Section 2 presents a brief description of the Colombian institutional context, and Section 3 describes the administrative data, including the reconstruction algorithm for bureaucrat’s family networks and full career paths. Section 4 documents four data facts on family connections, while Section 5 estimates the returns of family ties to top bureaucrats and examines the qualifications of those receiving them. Finally, Section 6 evaluates the anti-nepotism legislation and the strategic response of bureaucrats, while Section 7 concludes.

2 Institutional Background

The Colombian public sector has more than 1.2 million public servants. This workforce accounts for more than 10% of the formal employment in the country and its wage bill represents around 18% of total public sector expenditure. According to the Administrative Department of the Civil Service of Colombia, bureaucrats, teachers and frontline providers account for 70% of these jobs, while the remaining 30% correspond to active members of the police and military forces. For the purpose of this paper, I focus on the universe of workers in the first group across all branches of the government, including *contractors* and *civil servants* at all hierarchical levels (*managers, advisors, professionals, technicians, and clerical workers*).

2.1 Job allocations

There are three paths to become a public servant in Colombia. The first is through a meritocratic process and civil service examinations. Workers who enter this way belong to the official career system and earn tenure after a trial period of six months.

The second path is through direct hiring as a contractor. Typically, public sector agencies publicly announce specific consultancy services or tasks they need to fulfill. Indi-

viduals who satisfy these requirements compete for the position based on experience and education (no exams are required). Public sector managers and hiring committees select the best applicants according to the initial terms of reference and previous experience as contractors. If there are not enough applicants, or the contract value is sufficiently low, managers can directly hire individuals who they consider fit best the requirements without any further justification. Contractors do not belong to the career system nor to any hierarchical level, and have fewer benefits and stability conditions than bureaucrats who enter via civil service exams.¹⁴

The third entry path is through elections or direct appointments in positions of trust also known as *cargos de libre nombramiento y remocion* [free-appointment and dismissal]. These positions are held by managers and advisors who have themselves direct influence in the process of hiring and promotions of other bureaucrats within public sector organizations. Therefore, the turnover of these top bureaucrats depends on the discretion of government officials, election cycles, and the mandatory or voluntary retirement of workers.

2.2 Discretionary appointments and promotions

Two institutional features make Colombia an ideal laboratory to study nepotism in the public sector. On the one hand, while most *entry* positions in the public sector have to be allocated via exams and educational qualifications, today less than 50% of the *total* public sector employment is provided via meritocratic examinations. The abuse of direct hiring and parallel payrolls based on temporary positions and contracts have implied that, today, most of the selection and promotion of bureaucrats occurs via discretionary appointments. The problem is so widespread that most public sector agencies have a larger proportion of contractors than workers in the official career system, and contractors that are supposed to work for few months are usually in charge of core public sector activities for years.

On the other hand, the allocation of jobs through meritocratic processes is extremely slow and applies just to the recruitment of workers (*entries*) and *not* to the promotion or compensation of functionaries once they are inside the public administration.¹⁵ This implies that multiple positions, even when assigned meritocratically, have to be temporally filled by provisional appointees (*encargados* or *provisionales*) selected directly by immediate superiors. Moreover, the ultimate decision on temporary leadership positions and coordination tasks — that usually comes with temporary bonuses and leadership premia — are not regulated by any meritocratic process.

Therefore, moving up the ladder without the favor of top bureaucrats (managers and advisors) is difficult. In fact, hierarchical promotions in the public sector are rare — less than 4% of the career transitions per year — and depend either on 1) a fixed pay grade

¹⁴Contractors have to contribute independently to the pension and health systems. They cannot be unionized and are usually hired for shorter periods (typically less than two years) without any guarantees that the public administration will renew their contract in the future.

¹⁵Bureaucrats who want to be promoted can only apply to entry level vacancies available in their institution, where they have to compete with other workers inside and outside the organization. This scheme restricts their possibilities and does not account for their expertise or progress within the institution.

scheme based on experience or education, or 2) the direct influence of powerful connections.

2.3 Anti-nepotism laws and the constitutional amendment of 2015

As in many other countries,¹⁶ appointing relatives in the public sector is illegal in Colombia. According to the original version of the 1991 Constitution,

[Article 126] “Civil servants may not appoint as employees, individuals to whom they are kin up to the fourth degree of consanguinity, second degree of affinity or the first degree of civil status, or with whom they are bound through marriage or permanent union. Neither may they designate individuals linked through the same ties to whom intervened in their designation [...]”

The punishment for appointing family members is severe. It includes not just the removal of both sides involved in the nepotistic hiring but also, depending on the resources compromised, the payment of fines and imprisonment between five and twelve years.

De jure, the auditing of these family connections occurs during the hiring or promotion of any public sector worker. The human resources office and the office of internal oversight within each organization are in charge of this process. They approve and verify the mandatory reports of family connections filed as part of the conflict of interest reports and investigate any potential conflict directly identified by them or through any allegation made to the office.¹⁷

De facto, however, the auditing relies only on the confidential disclosure of all family members in the first degree of consanguinity or affinity. This feature has restricted the auditing scope to immediate family connections and limited the inspection of family ties to siblings, nephews, grandparents, uncles, cousins, and beyond, only to cases where denounces of corruption to the internal oversight office in each institution are made.

Between 2013 and 2014 various scandals involving multiple members of the judiciary system¹⁸ and the Attorney General¹⁹ uncovered a set of loopholes with this piece of legislation and its enforcement. The subjective interpretation of the article led open the possibility of indirect hiring and promotions. Bureaucrats in powerful positions were able to nominate their relatives to selection committees or to suggest their names to other managers that subsequently make the appointment. Similarly, they were also able to appoint relatives just before leaving office who could then re-appoint them back later through other indirect mechanisms. Moreover, the law was interpreted sometimes to apply only to employees in the official career system and not to temporary contractors.

As part of other constitutional reforms and partially motivated by these scandals, Congress approved a constitutional amendment that modified the original constraints of the 1991 constitution. The Legislative act 02 of 2015 modified the original anti-nepotism law as follows

¹⁶See Appendix Table A-1.

¹⁷Every disciplinary investigation has to be reported to the Attorney General’s office. If it ends up in a disciplinary sanction, the Attorney General’s office is in charge of investigating additional charges linked to the sentence.

¹⁸See, for instance, <https://www.elspectador.com/judicial/se-acabo-el-yo-te-elijo-tu-me-eliges-articulo-500628/>, accessed in March 2019.

¹⁹See, for instance <https://www.semana.com/nacion/articulo/rodrigo-uprimny-habla-sobre-el-fallo-contra-el-procurador-ordonez/493381/>, accessed in June, 2021.

[Article 126] “Civil servants may not in the exercise of their functions, nominate, propose or contract people within their kinship up to the fourth degree of consanguinity, the second level of affinity, the first level of civil status, or with whom they are linked by marriage or permanent union. They will not be able to nominate or propose as civil servants, nor celebrate state contracts with, people that have intervened in their postulation or designation, nor with people that have with them the same bonds described in the previous item. [...]”

The law henceforth applied to all public sector appointments, including contract workers.²⁰

In the last part of the paper, I use this policy experiment to study the effectiveness and responsiveness of this anti-nepotism legislation in Colombia.

3 Data construction

Identifying nepotism in the public sector is challenging. Ideally, one needs to observe family connections between public sector workers and their career progression within organizations. This paper builds upon a large-scale consolidation and digitization of multiple administrative datasets and a novel family network reconstruction methodology that overcome these empirical challenges. This section describes each of these data sources and details the data construction process of bureaucrats’ full career paths and extended family networks.

3.1 Panel data on public employment outcomes

I collect and combine employer-employee records and detailed biographical information from three administrative datasets to reconstruct the career paths of bureaucrats over time.

First, I undertake an extensive data categorization of more than one million civil servants’ curricula vitae. The data come from mandatory annual reports of CVs to the *Sistema de Informacion y Gestion del Empleo Publico* (SIGEP).²¹ This system includes data on the demographics, levels of education, work experience, and pay grade of all bureaucrats in Colombia. It covers all state workers from the three branches of government, excluding only the military, the police force, and individuals elected by popular vote. For each one of the 9,417,400 job-spells listed as work experience in these CVs, I categorized whether they corresponded to a public or a private sector job. For public sector spells, I further code the location, governmental agency, and hierarchical level where these took place.²² Since I have

²⁰Moreover, following the OECD standard, the Administrative Department of the Public Service complemented this reform by creating a unique Public Integrity Manual aimed to standardize the process of assessment and oversight of the conflict of interests including a normalized procedure to identify, limit and report any real or apparent conflict of interests including the favoring of relatives in the public sector. See, in particular, <https://www.funcionpublica.gov.co/documents/36031014/36151539/Guia-identificacion-declaracion-conflicto-intereses-sector-publico-colombiano.pdf>, accessed on July 17, 2021.

²¹All the information uploaded to the system is declared under oath and must pass a rigorous verification process from HR in each organization before each worker gets hired or can renew or sign a new contract. Official documents that support the CV records, such as diplomas and private and public experience proofs, remain in the system as pdf attachments that can be checked at any time by the Department of Civil Service or any judicial authority. The CV information is partially available online for public scrutiny at <http://www.sigep.gov.co/>. Appendix Figure A-4 shows a commented screenshot of the information available in that website. Given the nature of the biographical data, I observe the full career path of bureaucrats starting with their entry into the labor force and regardless of whether they worked in the private or the public sector.

²²Since records are created upon entry and updated annually, I verify the public sector classifications of early periods using later employer-employee records and CVs. Furthermore, I fill any gaps and correct inconsistencies in the records across multiple reports. This implies that I can go backwards and recover job-spells and workers that were not reported or updated initially into to the system. This is a key feature of the data since the deployment of the SIGEP was gradually adopted across public sector institutions.

access to the non-anonymized version of this data, I also have information on the full names, sex, date and place of birth, and national identification numbers (*cedulas de ciudadanía*) of all bureaucrats.

Second, I complement the job-spell data using information from all contractors hired by any public sector institution. I use more than 6,345,000 contract records from the *Sistema Electronico para la Contratacion Publica* (SECOP), the public procurement information system established by the Colombian central purchasing body, to digitize all the transactions held by public entities in the country.²³

Third, I incorporate information on total earnings from the *Planilla Integrada de Liquidacion de Aportes al sistema de seguridad social* (PILA), an employer-employee dataset providing detailed information on the formal employment and total earnings.²⁴

The resulting dataset is a balanced half-yearly²⁵ panel dataset of $N = 15,151,823$ observations containing information on the full career paths of $n = 1,083,714$ ever public servants from 2011 to 2017. The sample is restricted to individuals between 18 and 59 years old in 2011.²⁶ This leads to a balanced panel of $N = 13,984,555$ observations and $n_b = 1,000,112$ bureaucrats. I further divide these observations into two groups of individuals ($n_b = n_{top} + n_{ntop}$), those who are or become top-bureaucrats (managers or advisors) at some point in their careers ($n_{top} = 175,792$) and those who do not ($n_{ntop} = 824,320$).²⁷

Table 1 presents key descriptive statistics.²⁸ And Appendix Figure A-3 plots the hierarchical composition of the public sector jobs over time. Top bureaucrats (managers and advisors) represent 13% of the public labor force and are, on average, more educated than non-top bureaucrats. For example, 48.5% hold a post-graduate degree, compared to the 18% among those who never become top bureaucrats. Bureaucrats enter the public sector when they are, on average, 29 years old and are 34 at the beginning of 2011.²⁹ There is a lot of variation in public and private sector experience and dispersion in wages. However,

²³I use the procurement data from both web-based systems SECOP I and SECOP II. These were created and maintained by Colombia Compra Eficiente (CEE) and can be accessed online at <https://www.colombiacompra.gov.co/secop>. I use institutions' unique IDs (NITs) and the national identification numbers of contractors (*cedulas de ciudadanía*) to 1) verify and expand the job-spell data in the CVs for those who were contractors at some point during their careers, 2) fill any data gaps for workers that reported being contractors in the public sector but did not specify enough details in their CVs to classify their employment.

²⁴Unfortunately, using information from the SIGEP or the PILA only is not enough for the empirical strategy. The PILA system does not provide information on the worker's hierarchical position once they get into the public administration or any private or public sector experience in the past. On the other hand, as opposed to SIGEP, PILA records actual earnings instead of fixed salary tables, a feature that is critical since wage changes through coordination or leadership premiums, as well as, extra hours would not be reflected in the salary tables.

²⁵In principle, I could create a panel at the weekly or monthly level. However, since most of the hiring and promotions occurred at the beginning of the fiscal year and most contracts are for six or twelve month I defined the time unit of the panel as half-year. This aggregation also has the advantage of reducing substantially the time of estimation of the main regressions without losing too much statistical power.

²⁶This procedure excludes all individual-time pairs with bureaucrats unable to work for deterministic age restrictions. In Colombia, the legal working age to enter into the public sector is 18 years old. The mandatory retirement age for public servants in Colombia by 2011 was 65 years old. Appendix Figure A-6 presents the age distribution of all ever bureaucrats.

²⁷It is important to clarify at this point that even though I restrict the sample of analysis to only all non-top bureaucrats, There are still workers in middle and lower tier managerial positions. However these do not have any direct influence on public employment outcomes since they are not responsible of recruitment and I am not currently able to identifying differences in a particular sub-layers of the hierarchy.

²⁸See Appendix Table A-3 for additional summary statistics at the individual level.

²⁹The distribution of ever bureaucrats age in 2011 is presented in Appendix Table A-6.

promotions and job separations are rare,³⁰ and therefore, the hierarchical composition is very stable across years. Around 40% of the public servants are contractors, and there has been a significant increase in the participation of professionals over time, moving from 22% in 2011 to 33% in 2017.

3.2 Family network reconstruction

To uncover the hidden family networks within the public sector, I exploit confidential information on family connections recorded for the universe of bureaucrats. This dataset comes from the classified disclosure of family members in the first degree of consanguinity and affinity that all civil servants have to report to the Administrative Department of the Public Service (DAFP). Bureaucrats file this mandatory requirement before entering the public sector and as part of the conflict of interests declaration collected by the DAFP. This report must be updated annually, including each family member’s national identification number, full name, gender, and date of birth, regardless of their labor force participation or sector of employment.³¹

The family network reconstruction proceeds in two steps, summarized in Figure 1. It starts by making an undirected network representation of the family members of each bureaucrat using the annual reports of family ties. In this representation, nodes identify individuals, and edges symbolize dyadic family linkages of one degree of consanguinity. Each one of these connected components represents a family. I combine these clusters *within each year* based on the national identification numbers and the entire set of demographics from all reported and filling individuals. Using the demographic information, I am able to correct for voluntary and involuntary typos in the national identification numbers and merge nodes representing the same individual.³² With this procedure, I recover or simplify 28,343 family linkages. This leads me to 1,068,750 family clusters containing a total of 2,464,868 individuals. I refer to this graph of connected components as the Official Data since it is what human resources could potentially observe each year using the reports.

In the second step, I combine these resulting clusters *over time*. This key step enables me to uncover connections that were not observable in any of the year-specific snapshots. This procedure tempers the concern that newcomer bureaucrats strategically misreport family members who are (or were) part of the public administration and who, therefore, could potentially generate a conflict of interest at the moment of their entry. In this second step I recover 796,349 family linkages. The resulting graph, which I name Real Network, identifies 761,231 families (or connected components), containing a total of 2,446,904 individuals.

³⁰Promotions and separations account for 3.3% and 3% of all transitions over time, respectively.

³¹Crucially, the system just allows the addition of family members but not their elimination. In fact, the report of a family member generates a unique instance in the system that creates a permanent link between the bureaucrat and his/her family member, even after divorces or the death of a family members.

³²I use multiple record deduplication algorithms for this process. See, for example, <https://recordlinkage.readthedocs.io/en/latest/about.html> as well as the Networkx python package to create and combined the family networks.

Two features of this final dataset of family connections are worth noting. First, family network topologies are fixed once reconstructed. No nodes disappear or are added during the empirical analysis, and no connections are created or destroyed over time. The latter, of course, since blood connections are predetermined.³³ Second, nodes can have two mutually exclusive states in each period. They are either bureaucrats or non-bureaucrats. Based on this representation, I can identify the degrees of consanguinity between any pair of individuals within a family using Dijkstra’s shortest path algorithm (Dijkstra, 1959). More importantly, I am able to calculate the degrees of separation (consanguinity) between nodes with different states or characteristics at any given point in time.

Panel A in Figure 2 presents the distribution of connections per node before and after the second step of the reconstruction. Notice that, on average, the matching algorithm adds one connection per node and that most of the recovered connections come from individuals who initially reported one or zero connections. This critical addition, however, uncovers plenty of additional extended family connections. Panel B in Figure 2 shows the distribution of family sizes (number of nodes per connected component) before and after the second step. Even though I am adding, on average, just one additional family member per cluster, the distribution of family sizes shifts sharply to the right. Appendix Figure A-7 shows, for example, how the largest family network reconstructed based on the Official Data significantly differs in shape and size from the most extensive family in the Real Network.

3.3 Performance Indicators

Measuring performance in the public sector is not trivial. Any meaningful measure has to be comparable across agencies, workers and positions, and must be relevant to the ultimate goal of each institution. I overcome these challenges by leveraging three novel data sources.

First, I gather official information on records of individual misperformance. The data comes from web scraping the online version of the *Sistema de Informacion de Registro de Sanciones y Causas de Inhabilidad* (SIRI), a system created by the Office of the Inspector General of Colombia to keep the records of all prosecutions and investigations carried out by this office against public officials. It includes violations of the disciplinary code, the involvement in cases of corruption, and every legal impediment generated by those records over time.³⁴ With these, I create time-varying indicators of any report of misperformance and active impediments. Even though these measures do not speak directly to the productivity of bureaucrats, they capture an important dimension of the quality of the labor force: the integrity and eligibility of the public servants to fulfill their public sector duties.³⁵

Second, I use information on agencies’ performance from the *Medicion del desempeno Institucional* (MDI) database, a publicly available resource which builds on annual reports

³³Connections involving spouses however, could be potentially endogenous to public sector outcomes. In Appendix A, I describe how this could affect my results and how I deal with this potential identification issue.

³⁴Records include forced dismissals, suspensions, disciplinary warnings, fines, reprimands, arrests, forced termination of the employment contract, among others.

³⁵All positions in the public sector require having a clean record before entering into a new position. However, once inside, these records are rarely used to determine the appropriateness for promotions or wage increases.

of achievement of more than 3,800 agencies in the public sector. This database, managed by the Administrative Department of the Public Service, uses questionnaires given to the most important authorities within each institution to rate the capabilities and achievements of each organization. It evaluates their ability to provide public goods and services based on multiple indicators of administrative capacity. I focus my analysis on the agency’s overall performance index in 2016 represented by a score between 0 and 100.

Finally, to complement and externally validate the previous index, I use independent information collected by Transparency International through the *Indice de Transparencia de las Entidades Publicas* (ITEP) for the 251 most representative public sector agencies in Colombia. I use reports for 2014 and 2016 that, similar to the MDI, rank agencies using a score between 0 to 100 based on the transparency and institutional capability of each agency.

4 Stylized facts

I start the analysis by documenting four empirical facts about the presence of family connections in the public administration.

4.1 Fact I — Recovered linkages

Table 2 summarizes the percentage of family linkages recovered after each step of the reconstruction algorithm described in Section 3.2 as well as the distribution of family connections before and after this procedure. I find that about 26% (219,478 out of 824,692) of the uncovered linkages come from connections between family members in the first degree of consanguinity who are, or eventually become, public servants between 2011 and 2017. This means that more than a fourth of the recovered linkages occurred between children and parents or between couples that could have being part of an illegal connection and who were invisible for the Human Resources Department checking only the raw data for any potential conflict of interests.³⁶

4.2 Fact II — Pervasiveness of Family Connections

Figure 3 presents the fraction of bureaucrats for which I can identify a family connection within the public administration. The figure differentiates whether the connection occurs within the same institution or not and whether it includes a top bureaucrat (i.e., a manager or an advisor) or not. Around 38% of bureaucrats have a relative in the public administration at any point in time, while 18% have a family connection to a top bureaucrat. More importantly, about 11% of bureaucrats have a family connection within the same institution they are working in. Among those, 2% to 3% involve a top bureaucrat.³⁷

³⁶See Section 2.3 for a description of the anti-nepotism legislation and how this auditing process is implemented.

³⁷Appendix Table A-5 zooms in to these internal connections and presents the summary statistics on the number of family connections (per ten thousand employees) that occur within the same institution across all branches of the government and levels of centralization. The table only counts family connections among bureaucrats with different hierarchical positions to account for the power differentials that could lead to kin favoritism. Despite the heterogeneity across agencies, I find that family connections within the same institution are common, especially if those connections involve relatives below four degrees of consanguinity.

4.3 Fact III — Average degree of consanguinity between bureaucrats is small

Figure 5 presents the distribution of the average consanguinity degree between bureaucrats across all families in my sample. To construct this distribution, I calculate within each family the average path length between public sector workers at each point in time, and its average over all the periods in which at least two family members were working in the public sector at the same time. More specifically, I compute:

$$(1) \quad C = \frac{1}{T} \sum_{t=1}^T \frac{1}{N_t(N_t - 1)} \sum_{i \neq j} d(i, j) \cdot \mathbb{1}(i \text{ and } j \text{ are bureaucrats at } t),$$

where $d(i, j)$ is the shortest path length (in degrees of consanguinity) between individuals i and j , N_t is the number of individuals who are bureaucrats in family f at time t , and T the number of periods in which there are at least two bureaucrats within the family.

I find that the average consanguinity degree between bureaucrats is small, about 2.61, and that the distribution of these average path lengths is mostly concentrated below four degrees of consanguinity.

4.4 Fact IV — The potential costs of family connections

In Panel A of Table 3 I report the beta coefficients of the partial correlation between the overall performance index of agencies in 2016 and the number of family connections up to four degrees of consanguinity according to the following econometric specification,

$$(2) \quad \text{Index}_k = \rho_0 \cdot \left(\frac{\text{CloseTies}_k}{\text{Employees}_k} \right) + \rho_1 \cdot \text{Employees}_k + \rho_2 \cdot \text{CloseTies}_k + \gamma_{n(k)} + \epsilon_k,$$

where k indexes agencies, Employees_k is the total number of individuals working at institution k per one thousand employees and CloseTies_k is the total number of family connections up to four degrees of consanguinity. Finally, $\gamma_{n(k)}$ is a full set of fixed effects depending on different levels of agencies' aggregation $n(k)$.

Regardless of the degree of centralization by functions (*Centralized*, *Decentralized*, *Mixed*), the level of the administration (*National*, *Regional* or *Local*), the branch of the government (*Executive*, *Legislative*, *Judiciary*, *Oversight and control*, or *Autonomous*), and the legal nature of the agency (*Ministry*, *Administrative Department*, *Assembly*, *Alcaldia*, *Personeria*, *Gobernacion*, *Public Service Firm*, *Control Agency*, or *Public Sector Company*), I find that larger shares of close family connections are associated with lower levels of institutional performance.

Since government reports about their own progress might be heavily upward biased, I estimate identical specifications in Panel B of Table 3 using the independent assessment from Transparency International (TI) about the overall performance of most representative agencies in the public sector in 2014 and 2016. Even though the sample of institutions covered by TI is significantly smaller and the coefficients of interest are — as expected —

much larger, the qualitative results hold both across panels and specifications. The last column of Panel B shows that a one standard deviation increase in the number of close family connections is robustly associated with a decrease of 0.24 standard deviations in the performance index, even after controlling for a full set of time fixed effects and all levels of aggregation.

4.5 Summing-up

Taken together, these four stylized facts highlight the pervasiveness of family connections within the public sector in Colombia and the likely presence of illegal — and strategically misreported — connections according to the anti-nepotism legislation described in Section 2.3. Moreover, the strong negative relationship between the presence of close family connections and the performance of public sector institutions provides a first approximation of the potential costs of nepotism and further motivation for the analysis that follows.

5 Estimating the returns to Nepotism

I move now to the estimation of the average nepotistic return of family connections. I focus on the returns of being family-connected to top *non-elected* bureaucrats in terms of total earnings and promotion probabilities. Studying only middle- and lower-tier bureaucrats already in the public administration, I ask whether workers who become family-connected to public sector managers or advisors end up receiving any career premium. This is a key check for the analysis of nepotistic behavior.

5.1 Empirical Strategy

The identification strategy in this subsection exploits quasi-experimental variation in family connections generated by the turnover of top bureaucrats across public sector agencies. To do so, I estimate for bureaucrat i in family f and time t ,

$$(3) \quad E_{i,t} = \theta_i + \delta_t + \eta \cdot \text{TopConnected}_{f(i),t} + \mathbf{X}'_{i,t} \boldsymbol{\Phi} + \xi_{i,t}$$

where $E_{i,t}$ represents public employment outcomes such as total earnings or an indicator for a hierarchical promotion, and $\text{TopConnected}_{f(i),t}$ is a dummy variable that equals to one if worker i from family f has a family connection to a top manager or advisor at time t . By including bureaucrat fixed effects θ_i , I only exploit within-bureaucrat variation in family connections triggered by the turnover of top bureaucrats. These effects also allow me to control for any unobserved individual-specific characteristic related to family connectedness, such as inherited or innate ability, family backgrounds, initial public service motivation, occupation, and any other individual time-invariant preference that could be directly affecting public employment outcomes. The identification of my parameter of interest, η , then comes from bureaucrats who experienced changes in family connections to top bureaucrats during

their careers.³⁸

Given that most salaries and promotions in the public sector depend deterministically on years of experience and levels of education, I control for, $\mathbf{X}_{i,t}$, a vector of individual time-varying controls including public and private sector experience of worker i since her entry into the labor force, which are allowed to flexibly evolve over time by her level of education. Moreover, since managerial turnovers occur across multiple agencies, and top bureaucrats are more likely to influence outcomes within the agency they work in, the preferred specification is given by,

$$(4) \quad E_{i,t} = \theta_i + \delta_t + \gamma_{k(i,t)} + \eta \cdot \text{TopConnected}_{f(i),k(i,t),t} + \mathbf{X}'_{i,t}\Phi + \xi_{i,t},$$

where $\gamma_{k(i,t)}$ represents a complete set of agency fixed effects controlling for all time-invariant characteristics affecting both connectedness and labor market outcomes.³⁹ These include, for example, the organizational structure of agencies, the geographical location of institutions, and agency-specific pay grades or compensation schemes. Furthermore, by including time fixed effects δ_t , I address the concern that unobserved and aggregate common shocks such as general elections, national reforms, or macroeconomic policies can explain the relationship between public employment outcomes and family connections to top bureaucrats. Lastly, $\xi_{i,t}$ represents the error term which I cluster at bureaucrat-agency level or at the dyadic family-agency level corresponding to the effective sources of identifying variation. To simplify the notation in subsequent sections, I define $\text{TopConnected}_{f(i),k(i,t),t} \equiv B_{f,k,t}^{\text{top}}$.

5.1.1 Main identification assumptions and key threats to identification

Notice that to identify my parameter of interest, I do not need to assume that top bureaucrat turnovers occur at random. Instead, to consistently estimate η for each outcome of interest, the econometric specification in Equation 4 requires that across agencies and $\forall t \geq 2$,

$$(5) \quad \mathbb{E}[E_{i,t}(0) - E_{i,t-1}(0) | \mathbf{X}_{i,t}, B_{f,k,t}^{\text{top}} = 1] = \mathbb{E}[E_{i,t}(0) - E_{i,t-1}(0) | \mathbf{X}_{i,t}, B_{f,k,t}^{\text{top}} = 0]$$

In other words, that labor market outcomes would have exhibited parallel trends in the absence of those connections. This condition ultimately requires that there are no additional unobserved time-varying and individual-specific characteristics correlated with family connectedness that could have explained the changes in labor market outcomes of individuals over time.

Since family connectedness is pre-determined by consanguinity relationships and the turnover of managers and advisors generates cross-sectional variation in family connections

³⁸Notice that comparisons of connected vs. non-connected individuals without using within-bureaucrat variation in family connectedness would lead to misleading results. These comparisons would disregard key confounders leading to overestimates of the actual return of family ties. For instance, the presence of family-specific characteristics, centrality of workers in the family network, common labor shocks, as well as, inter-generational transmission of 1) preferences 2) human capital, or 3) earning capacity that could explain why certain family members are more likely to work within the public sector or choose to stay in the same occupations, positions or agencies.

³⁹ $k(i, t)$ is a function that maps for each individual i and time t the agency where the bureaucrat works, while $f(i)$ is a function that maps each individual to her corresponding family.

to *all bureaucrats* within each agency, it is unlikely that some unobserved and individual specific factor could violate this condition without affecting other bureaucrats within the agency. Nevertheless, I can validate the plausibility of the assumption by estimating for each outcome of interest the more demanding and fully dynamic event-study specification,

$$(6) \quad E_{i,t} = \theta_i + \delta_t + \gamma_k + \eta_{-5} \sum_{\ell \leq -5} B_{f,k,\ell}^{top} + \sum_{\ell=-4, \ell \neq 2}^4 \eta_{\ell} \cdot B_{f,k,\ell}^{top} + \eta_5 \sum_{\ell \geq 5} B_{f,k,\ell}^{top} + \mathbf{X}_{i,t}' \boldsymbol{\Phi} + \xi_{i,t},$$

where η_{ℓ} captures the effect of a family connection to a top bureaucrat ℓ periods before or after a managerial turnover creates a change in family connectedness. This specification allows me to test directly for the presence of pre-trends in labor market outcomes and look at the dynamic effects of getting a family connection to a top bureaucrat.

Two key additional assumptions are implicit in the empirical models described above. One is that the treatment effects of family connections to top bureaucrats are homogeneous across individuals and agencies, and the other is that effects of gaining and losing a connection are symmetric over time. Recent developments in the applied microeconomics and econometrics literatures (Goodman-Bacon, 2021; Sun & Abraham, 2020; de Chaisemartin & D’Haultfoeulle, 2020) have shown how the violation of these implicit assumptions may lead to highly biased estimates and misleading tests for the parallel trend assumption.⁴⁰ In fact, in the presence of treatment heterogeneity, Ordinary Least Squares estimators of Equations 4 and 6 — *even after partialling-out agency fixed effects* — could lead to non-significant or even negative average treatment effects, when all individual specific effects are positive and significant. The key reason behind this identification issue is that under treatment heterogeneity and non-staggered treatment adoption, Two-Way Fixed Effects regressions (TWFE) end up using already treated units or switchers as controls. These comparisons create a mechanical negative weights problem during the computation of the final average treatment effect, that in turn, produce biased estimates of the true coefficients of interest.⁴¹

To address these important identification concerns, I follow two strategies. First, I estimate Equation 4 focusing on the treatment of ever having a connection to a top bureaucrat — *by construction a staggered treatment* — and include as pure controls individuals who have never been family-connected to a top bureaucrat over time. This exercise tempers the concerns that using TWFE would end up employing the set of switchers as controls, but also captures the idea that the first connection to a top bureaucrat could structurally change

⁴⁰More specifically, they could incorrectly test the absence of pre-trends in event studies since the contamination caused by the treatment heterogeneity can lead to estimates that are non-zero in the absence of pre-trends, or zero in the presence of pre-trends.

⁴¹I assess whether treatment heterogeneity is an important threat to identification in this context. To do so, I use de Chaisemartin and D’Haultfoeulle (2020) diagnostic tool to estimate the fraction of negative weights implied by Equation 3, and calculate the theoretical minimal value for the standard deviation of the treatment effects under which the actual average treatment effect of top family connections may have an *opposite sign* than the coefficient estimated by the original two-way fixed effect regression (TWFE). As reported in Appendix Table A-8 treatment heterogeneity is an issue to recover the parameters of interest in my context. I find that more than 18% of all treatment effects are associated with a negative weight, and that just an standard deviation of 0.015 in treatment heterogeneity across individuals can lead to average treatment effects of opposite signs than the ones obtained using simple TWFE coefficients.

the long-term career prospects of workers within the public administration. Moreover, using the same sample, I further provide the estimates of Equation 6 to test the parallel trend assumption under this setup and its corrected event study versions, based on the [Sun and Abraham \(2020\)](#) estimator.

Second, I account for the non-staggered nature of the family connectedness and embrace the potential asymmetry between gaining and losing a top bureaucrat connection. To do so, I follow [de Chaisemartin and D’Haultfoeuille \(2020, 2021\)](#) and report their proposed and corrected DID estimators that account for both treatment heterogeneity and treatment reversals. These exercises not only allow me to consistently estimate the parameter of interest, but to test whether the career prospects of connected bureaucrats were closely linked to the fate of their relatives as top bureaucrats (i.e., test whether workers who lose connections stop receiving those nepotistic premia).

5.2 Empirical results

5.2.1 Total earnings

Columns 1 to 3 in Table 4 present the impact of having a family connection to a top bureaucrat on the log of total earnings. Column 1 shows that individuals who end up having a family connection to these bureaucrats receive, on average, a positive and significant wage premium of 3.74%. This increase in wages is neither explained by individual-specific characteristics nor by common shocks affecting all public sector workers. In Column 2, I present the augmented specification controlling for time-varying private and public sector experience according to the highest level of education achieved by each worker. I find that even after controlling for these unique determinants of earnings in the public sector, a family connection to a top bureaucrat implies an average salary premium of 3.03%.

In Column 3, I explore whether the observed increase in earnings occurs by the allocation of family members across higher-paid agencies or by the increase of wages within institutions. To do so, I compare the results in Column 2 with a more demanding specification that includes a comprehensive set of agency fixed effects. Since the coefficients of interest do not significantly vary across these columns and wages are deterministically settled via pay grades within each institution, the mechanism that seems to support this salary premium is likely the allocation of temporary leadership positions, and provisional appointments to family members *within* instead of *across* public sector agencies.

Panel A in Figure 6 presents the corresponding event-study to these comparisons according to Equation 6. This figure is based on 34,887 first-time connections to top bureaucrats. There are two main takeaways from this figure. First, there is no evidence of pre-trends before the connection event. This result reassuringly validates my primary identification assumption since, on average, total earnings exhibited parallel trends before the top bureaucrat connection. Second, it shows that treatment effects are heterogeneous over time, and if anything, somewhat larger than the average treatment effect as time goes by. Top connected bureaucrats do not start experiencing a positive wage premium until six months

after their relative becomes top bureaucrat, and one year and a half after they experienced this connection, they earn a salary premium that steadily increases up to 5.5%.^{42,43}

The interpretation of these magnitudes is subject to objections since they focus on a specific form of staggered treatment: the event of being ever connected to a top bureaucrat. Even though these results imply that initial connections have a persistent effect on the career trajectories of the affected bureaucrats, they disregard the possibility that such impacts can be heterogeneous across individuals and agencies. Similarly, they do not account for the fact that some workers experience more than one connection during their careers or lose connections that are not necessarily symmetrical in their impacts. More importantly, they reject also the possibility that those never-connected individuals are inadequate controls since they may differ in many other dimensions with respect to those who have at least one top bureaucrat connection during their careers.

To account for all of these additional identification issues, in Panel A of Figure 7, I present the corrected DID_M estimator proposed by [de Chaisemartin and D’Haultfœuille \(2020\)](#), that uses a properly computed average treatment effect coming from all pairs of ‘clean difference-in-differences’ within the sample. This estimator is based on 95,758 switcher events.⁴⁴ I find that even after controlling for potential heterogeneity across individuals and allowing for treatment reversals, family connected bureaucrats still receive a positive wage premium of 2.33% in total earnings.

Despite its consistent sign and significance, the last estimate could still be biased if the ultimate effects across individuals are also heterogeneous over time. Since the results using just the first connections in Figure 6 points towards that direction, in Panels B and C of Table 7, I present separately the dynamic DID_ℓ effects of winning and losing a connection based on the [de Chaisemartin and D’Haultfœuille \(2021\)](#) dynamic estimator.⁴⁵ The results of this exercise show that once one divides the 95,758 switcher events into winning and losing connection events, the ultimate impact of getting a family connection to a manager

⁴²These magnitudes are consistent with previous studies looking at the role of family connections. For example, [Xu \(2018\)](#) in a similar empirical setting using historical data for the British Empire finds that a family connections to a secretary of the state during the period of patronage implies a 9.3% wage premium with respect to non-connected bureaucrats. This magnitude is also consistent to the role of family connections to another group of powerful public servants: Politicians. [Folke et al. \(2017\)](#) in a low-corruption setting find that a family connection to Swedish politician implies a 3% increase in total earnings with respect to the median income of full time workers in 2000, while [Fafchamps and Labonne \(2017\)](#) find that in the Philippines family connections to politicians lead to better paying occupations.

⁴³These results hold and are qualitatively similar to those using the alternative [Sun and Abraham \(2020\)](#) estimator that I report in Appendix Figure A-8.

⁴⁴These are events defined by when bureaucrats switch from unconnected to connected and from connected to unconnected to a top bureaucrat.

⁴⁵Recall that DID_M is a weighted average estimator, across time periods t and treatment values, of simple DID estimators comparing the evolution of outcomes from $t - 1$ to t , among individuals whose connectedness changes from $t - 1$ to t , and individuals whose connectedness status remains unchanged at both dates. In other words, DID_M estimates the average effect over time of getting connected or losing a connection on outcomes, only among individuals whose treatment switches compared to those for whom it does not during the same time window.

On the other hand, DID_ℓ is a weighted average estimator, across time periods t and treatment values, of simple DIDs comparing the evolution of outcomes from $t - \ell - 1$ to t , among individuals whose connectedness changed for the first time $t - \ell$ periods ago and the not-yet switchers. In other words, DID_ℓ estimates the effect of having switched connectedness for the first time ℓ periods ago compared to those who did not change their status of connectedness at that time. Notice, however, that I normalized my graphs with respect to the coefficients in $t = -2$, one year before the connection takes place, to keep consistency across the simple event-study specifications.

or advisor within the public sector is a salary premium of 5.9%. Crucially, Panel B of Figure 7 also shows that the prospects of these connected bureaucrats are closely linked to the fate of their relatives as top bureaucrats. The results show that following the exit of managers and advisors, previously connected bureaucrats experience a significant reduction in total earnings that more than offset the effects of winning a connection. Given that these estimators are conditional on remaining in the public sector, these effects are simply lower bounds of the actual impact of losing a connection since I am not accounting for any potential exits generated by losing a connection to a top bureaucrat.⁴⁶

5.2.2 Hierarchical promotions

Columns 4 to 6 in Table 4 present the impact of family connections to top bureaucrats on the likelihood of being promoted. The promotion indicator used as an outcome includes all transitions moving up the ladder of the public administration and a shift from being a contractor to a position within the official hierarchy.

It is necessary to clarify here that this outcome is not necessarily the extensive margin of the total earning increases explained above. In fact, raises in salaries without changes in the hierarchical levels driven by leadership premia, bonuses, or extra hours occur. Similarly, there are rank promotions that do not imply direct increases in earnings. Moving from contractor to a staff position in the status of a provisional worker, for example, is considered a rank promotion. However, even though interim workers enjoy most of the non-pecuniary benefits of an official career position, they do not necessarily receive a higher wage than the one they earned as contractors.

Column 4 indicates that individuals who ever have a family connection to a top bureaucrat are 1.4% more likely to be promoted. The effect is sizable since hierarchical promotions are rare. Compared to an overall 3.3% mean in the occurrence of rank promotions, having a family connection to a manager or an advisor implies an increase of almost 40% in the likelihood of being promoted. This result is neither explained by common shocks affecting all individuals or individual-specific characteristics, nor by differential public or private experience profiles (Column 5). After controlling for all agency-specific characteristics (Column 6), it is clear that most of the returns on this margin come from promotions within the same institution where the top bureaucrats work. However, given that compared to Column 5, the coefficients slightly varies, I cannot reject the hypothesis that some of those hierarchical promotions also occurred across agencies.

Panel B in Figure 6 presents the analogous event study according to the econometric specification in Equation 6. As before, there are two main takeaways from this panel. First, there is no evidence of problematic pre-trends before the connection event, validating the primary identification assumption for this outcome variable. Second, the effect on the probability of getting connected kicks in immediately at the period where the family connection

⁴⁶I interpret these last results with caution since there is some evidence of negative pre-trends in earnings that could suggest anticipation effects to the top bureaucrats' exit or the decrease in the top bureaucrats' power of influence close to their turnover.

occurs, increasing up to 1.75%, but in contrast to the impact on earnings, it decreases one year and a half after the event takes place.⁴⁷

Following the same arguments detailed above for total earnings, in Panel A of Figure 7, I present the DID_M estimate. Using this alternative estimator, I find that the average treatment effect is slightly smaller at about 1.21%, compared to the 1.34% in Column 6 of Table 5 (i.e., of about 35% with respect to the mean of promotions).

These results imply that the simple specification in Columns 6 of Table 4 is not affected as much by subsequent treatment reversals or individual treatment heterogeneity. Nevertheless, to account for the potential heterogeneity in the effects of connectedness over time, I present in Panels B and C of Figure 7 the dynamic DID_ℓ estimates separately for winning and losing a top bureaucrat connection. Two results are worth noting. First, there seems to be an overall symmetric effect between winning and losing a family connection on the probability of being promoted. Second, since immediate effects are, in fact, asymmetrical at $t = 0$ and there are more winning than losing events, the ultimate net result is consistent with the DID_M estimate of 1.21% found above.

5.3 Key robustness test and important sources of heterogeneity

5.3.1 Ruling out key alternative interpretations

While the absence of pre-trends and consistent signs across specifications alleviate concerns about time-varying individual-specific confounders, one alternative interpretation of my results is that the turnover and the subsequent change in connectedness is masking other common shocks affecting additional sources of social connectedness or coordinated behavior of bureaucrats. One might worry that the results are not only capturing the role of family connections to top non-elected bureaucrats, but reflecting, for example, the ultimate influence of politicians targeting entire clusters of families (i.e., simply reflecting patronage practices). Likewise, the results could be consistent with non-connected bureaucrats voluntarily sorting out from the choice pool of potential promotees once they face a managerial turnover. Finally, jointly determined responses of family members to other reforms at the agency level could be confounding my results.

To address these additional and valid concerns, in Table 5, I extend the results of Table 4 by including a complete set of family-time and agency-time fixed effects that account for any potential agency-specific or family-specific shocks. Reassuringly, the sign and significance of the coefficients of interest are unaltered. If anything, once I include family-specific shocks, the role of being family connected is significantly larger, for both hierarchical promotions and total earnings.

⁴⁷These results hold and are qualitatively similar to those using the alternative Sun and Abraham (2020) estimator that I report in Appendix Figure A-8.

5.3.2 The importance of the degree of consanguinity

Who are the family members who benefit the most from these family connections to top bureaucrats? Figures A-9 and A-10 present the baseline results depending on the degree of consanguinity between bureaucrats and top managers and advisors. Each sub-figure comes from an independent regression model following the econometric specification in Equation 6. However, I redefine $B_{f(i),k,\ell}^{top} \equiv B_{f(i),k,\ell}^{top,s}$ to be a dummy equal to one if worker i has had a family tie to a top bureaucrat at the degree of consanguinity s at institution k at relative period ℓ . I document the results for all degrees of separation from 1 to 6 and report the fully dynamic event-study set of coefficients.

There are two main takeaways from these figures. First, the effects on hierarchical promotions and earnings do not operate through close family connections such as parents, children, or spouses. They do not work either through distant family connections of more than six degrees of separation.⁴⁸ Second, in terms of earnings, effects are concentrated in connections between 2 to 4 degrees of consanguinity, while returns on hierarchical promotions are concentrated between 3 to 5 degrees. To guide the reader, Appendix Figure A-2 presents a table of consanguinity displaying the type of family connections representing these degrees.

These results imply that most of the estimated returns to family connections come from a clear violation of the anti-nepotism legislation in the country. More importantly, these private returns operate through relationships that are not easily or actively audited by human resources within each institution, since they only focus on the first degrees of consanguinity and affinity.

5.4 Better screening or pure favoritism?

Although most of the returns estimated above are already illegal according to the anti-nepotism legislation in Colombia, a question that emerges from my previous analysis is whether those returns are still consistent with better screening of workers. It could be the case, for example, that those higher earnings and probabilities of being promoted are simply reflecting compensation differentials in terms of bureaucrats' relative — prior or expected — performance, which top bureaucrats might identify better if promotees are family members.

Estimating whether managers and advisors screen and select better workers using family connections is, however, empirically challenging. For example, to study *pre-promotion* characteristics upon which managers made the promotion decision, it is necessary to observe 1) the criteria involved for all workers considered in the decision and 2) determine the pool of candidates among which managers and advisors picked who to promote (if anyone). Similarly, to examine the selection in *post-promotion* performance, it would be necessary to observe the counterfactual accomplishments of those who were not promoted but were part of the choice set of candidates.

To overcome these challenges, I build on recent works by [Benson et al. \(2019\)](#) and

⁴⁸The null result for family ties at degree one is not completely surprising since connections of such degree are precisely the ones audited by human resources every year.

Voth and Xu (2021) to estimate the difference in pre-promotion characteristics and quantifying the selection effects in promotions. I describe the two approaches below.

5.4.1 Differences in pre-promotion characteristics

I start by evaluating the decision process that top bureaucrats face when looking at pre-promotion qualifications. To do so, I start by approximating the candidate pool of workers that public sector managers observe every period, as follows,

- i) For each time and agency, I restrict the panel of workers to all unpromoted bureaucrats in the public administration, some of whom are about to be promoted.
- ii) I further restrict the panel of workers to only agencies and choice-periods where at least one promotion was made from 2011 to 2017.
- iii) After a promotion takes place, I assure that promoted workers leave the candidate pool for subsequent periods. Therefore, promoted workers are used only to compute differences within the choice-period that they were promoted.

Using this new dataset, I evaluate the decision that managers and advisors made by calculating the differences in bureaucrats' pre-promotion characteristics ($Q_{i,t}^{pre}$) between promoted and passed-over bureaucrats and its relation with family connectedness. Formally, in the spirit of a balance test, I estimate for bureaucrat i and choice-period t ,

$$(7) \quad Q_{i,t}^{pre} = \lambda_{l \times h \times k \times t} + \mu_1 \cdot P_{i,t} + \mu_2 \cdot B_{f(i),k,t}^{top} + \mu_3 \cdot [P_{i,t} \cdot B_{f(i),k,t}^{top}] + \epsilon_{i,t},$$

where $P_{i,t}$ is an indicator of a promotion (hierarchical or via earnings) and $B_{f(i),k,t}^{top}$ is an indicator of a family connection between bureaucrat i and a top bureaucrat at agency k at choice-period t . Importantly, the characteristic $Q_{i,t}^{pre}$ is predetermined and measured in pre-choice-period $t - 1$. Crucially, the full set of fixed effects $\lambda_{l \times h \times k \times t}$ restrict comparisons only among groups of workers within the same choice-period t , agency k , hierarchical position h and seniority level l .⁴⁹ To account for serial correlation in outcomes and for the fact that not-yet promoted bureaucrats are observed over multiple choice periods, standard errors $\epsilon_{i,t}$ are clustered at the bureaucrat level.

The parameters of interest in Equation 7 are μ_1 and μ_3 . The first one estimates how fair or meritocratic the promotion of bureaucrats is relative to the characteristics of passed over workers at the moment of promotion. When $Q_{i,t}^{pre}$ represents a desirable qualification, a positive and significant μ_1 would capture how promotees positively differ from other candidates in the choice set, and therefore, how merit-based that promotion was. On the other hand, μ_3 estimates whether such effect diverges or amplifies when workers happen to be family connected to a top bureaucrat at the moment of promotion. Therefore, μ_3 captures the selection effect of connected promotions in pre-promotion characteristics.

⁴⁹I create 5 year bins in terms of bureaucrat's age starting at 18 years old. The results are robust to use age-specific categories or to control flexibly for age.

Table 6 presents the results for both types of promotions: hierarchical promotions in Panel A and pay raises in Panel B.⁵⁰ I focus on four pre-promotion characteristics. Column 1 shows the estimated coefficients from Equation 7 when looking at whether bureaucrats had any record of misperformance as an outcome. This indicator variable is equal to one if the bureaucrat had been dismissed, suspended, or had an admonition as a consequence of a disciplinary process in the public sector. Similarly, Column 2 looks at the indicator of having an active inability to work in its current position due to a past criminal, disciplinary or fiscal investigation. On the other hand, Column 3 uses an indicator variable equal to one if the bureaucrat has a higher educational attainment than the one required for his current position,⁵¹ and therefore whether the bureaucrat exceeds the expectations in terms of education. Finally, Column 4 uses the ratio between public sector experience (in semesters) and the total work experience as the outcome.

The estimated coefficients convey two key messages. First, movements up the ladder are, in general, merit-based. Promoted bureaucrats are, on average, less likely to have previous records of misperformance, active inability causes, and tend to have more relevant experience and education than passed over bureaucrats. However, these effects are in most cases reversed or heavily attenuated when promotees happen to be family connected to a manager or advisor at the moment of promotion. In other words, even though managers and advisors help to promote better-suited individuals relative to other available and similar candidates, they are also more likely to overlook these qualifications when promoting family members.

6 Evaluating the impacts of Anti-Nepotism legislation

The previous sections show that family connections to public sector managers and advisors significantly distort key public employment outcomes. Top bureaucrats extract private rents in terms of earnings and promotions for their family members and hinder the selection of more qualified public sector employees.

What can regulatory agencies do to tackle this issue? Is anti-nepotism legislation any effective at preventing this behavior? This section assesses whether introducing a more comprehensive anti-nepotism legislation mitigates some of these distortions. To do so, I evaluate the impacts of the 2015 anti-nepotism legislation in Colombia that prohibited top bureaucrats from appointing, designating, nominating, and contracting (directly or indirectly) any family member up to the fourth degree of consanguinity.⁵²

⁵⁰When running the regressions for wage promotions, I also include further interactions with fixed effects on initial wage bins defined by the quintiles of earnings within each agency and choice period. These allow me to compare workers with a similar wage at the moment of promotion.

⁵¹For clerical workers, this variable equals one when the worker has any level of education above high school. Similarly, for technicians, this variable equals one if they have a college education or more. In the case of professionals, this variable equals one if they have a specializations' degree or more. Finally, since contractors generally do not need to satisfy any specific education requirement, I set this variable equal to one for contractors if they have a masters' degree or more. However, the qualitative results are robust to assume that contractors are never overqualified.

⁵²See Section 2 for detailed explanation about this policy change.

6.1 Empirical Strategy

I start by evaluating the immediate response of family connections to the policy change. To do so, I construct a biannual panel of public sector institutions from 2011 to 2017 in which each agency is represented by 16 observations (or bins) per period. These bins correspond to all degrees of separation from one to sixteen, based on which, I define and calculate $N_{k,s,t}$ as the total number of family connections per ten-thousand employees that exist at institution k , at degree of separation s , and time t .⁵³ Using this new database and dependent variable, I estimate the following empirical specification,

$$(8) \quad N_{k,s,t} = \beta \cdot \left[\underbrace{\mathbb{1}(t \geq 2015-II)}_{\text{Post Reform}} \times \underbrace{\mathbb{1}(s \leq 4)}_{\text{Illegal}} \right] + \delta \cdot \underbrace{\mathbb{1}(t \geq 2015-II)}_{\text{Post Reform}} + \lambda \cdot \underbrace{\mathbb{1}(s \leq 4)}_{\text{Illegal}} + \alpha_k + \xi_{k,s,t},$$

where α_k represents a full set of agency fixed effects and $\mathbb{1}(\cdot)$ are indicator variables. Here, β captures the impact of the reform for family ties restricted by the law, i.e., those below four degrees of consanguinity. In my preferred specification, I further account for institution-time fixed effects and degree of consanguinity fixed effects ($\gamma_{k,t}$ and λ_s , respectively) instead of the aggregate indicator variables of post reform and illegal connections. These fixed effects fully control for agency-specific shocks over time and the overall distribution of connections at different degrees of separation. I cluster standard errors $\xi_{k,s,t}$ at the institution-separation level in all specifications, which corresponds to the level of identifying variation in this case.⁵⁴

The identification assumption in this context is that, in absence of the anti-nepotism legislation, bins above and below the threshold would have exhibited parallel trends in the number of family connections within institutions. I can check the plausibility of this assumption by running the following event-study counterpart,

$$(9) \quad N_{k,s,t} = \sum_{\tau=2011-I, \tau \neq 2014-I}^{2017-II} \beta_{\tau} \cdot [\mathbb{1}(t = \tau) \times \mathbb{1}(s \leq 4)] + \lambda_s + \gamma_{k,t} + \xi_{k,s,t}$$

where I expect β_{τ} , with $\tau \in [2011-I, 2014-II]$ to be statistically indistinguishable from zero.

6.2 Empirical results

6.2.1 Number of illegal connections

Table 7 presents the main results of the policy evaluation for different combinations of the fixed effects. The main coefficient of interest is stable across all columns. My preferred

⁵³When constructing $N_{k,s,t}$ I only count the total number of family ties among bureaucrats with different hierarchical levels. I do this instead of counting all family connections to effectively capture the asymmetries of power that could lead to the excretion of favoritism.

⁵⁴To account for potential panel composition differences, I restrict the estimation sample in two ways. First, I focus on agencies with at least one family connection at any degree of separation over the whole period. Second, I just keep in the sample the institutions that “start” reporting information into the system before the policy change. This address the concern about the merge of institutions post reform and the differential timing in the adoption of the SIGEP. As these modifications are without loss of identifying variation since the discarded observations are uninformative conditional on the fixed effects included in the model.

specification in Column 4 shows that following the reform, the number of illegal connections per ten-thousand employees decreases, on average, by 9.1. Compared to the sample mean of 58.01, this implies a reduction by 15.6% in the total number of family ties below four degrees of consanguinity. Crucially, these results are neither explained by any common shock that is agency-specific nor by any time-unvarying characteristics at the degree of separation or agency level.

This result is conditional on the parallel trend assumption. In Figure 8, I present the corresponding event-study specification where I check the plausibility of this assumption. The estimated coefficients show that there are no significant pre-trends and, more importantly, reveal that the dynamic effects are stable over time and, if anything, slightly larger than the average effect reported in Table 7.

6.2.2 Differential impact across agencies

I present in Table 8 the results by grouping the set of agencies according to the branch of the government they belong to. Two main conclusions come from this table. First, illegal connections are more widespread in the Executive and Judiciary branches and less so in the Legislative Branch and among Autonomous, and Independent agencies.⁵⁵

Second, the impact of the reform is consistent with an overall reduction in family connections below four degrees of consanguinity. Notably, the effects are concentrated in the Executive and Judiciary branches where the majority of institutions are, and where the delivery of public goods occurs.⁵⁶

6.2.3 Differential impact across degrees of relatedness

According to Section 5.3.2, nepotistic returns are concentrated among family connections between 2 and 5 degrees of consanguinity. A natural question is whether the reform effectively reduced the presence of these most problematic connections. To test this possibility, following the same notation as in Equation 8, I estimate,

$$(10) \quad N_{k,s,t} = \sum_{\phi=1}^{15} \beta_{\phi} \cdot [\mathbf{1}(t \geq 2015\text{-II}) \times \mathbf{1}(s = \phi)] + \sum_{\phi=1}^{15} \lambda_{\phi} \cdot \mathbf{1}(s = \phi) + \gamma_{k,t} + \xi_{k,s,t}.$$

where λ_{ϕ} estimates the average number of family connections at degree of consanguinity ϕ before the law and β_{ϕ} captures the average change in family connections at the corresponding degree of separation post reform. The excluded category in this specification, and therefore the reference point for all these coefficients, is the bin of 16 degrees of consanguinity.

Figure 9 presents the estimated coefficients. There are two main takeaways from this

⁵⁵The autonomous and independent agencies include the Central Bank, regulatory agencies such as the office of the Attorney General, the *Superintendencias*, as well as public universities.

⁵⁶Appendix A-11 presents the associated event studies for the three main branches of the government, validating the identification assumption. These figures also confirm that most of the effects are coming from the reduction in family connections in the Executive and Judiciary branches. Even though there is a lack of significance for the effects on the Legislative branch, the event-study specification shows a rapid reduction in the number of illegal connections immediately after the introduction of the law.

figure. First, there was a significant decrease in the most common connections at degree one and two corresponding to a reduction of 44% and 16% respectively when compared to their sample mean.⁵⁷ Second, the reform was completely ineffective at reducing connections at degrees three and four. These results and those in Section 5.3.2 imply that, even though the policy had a significant impact on close family connections, it did not affected the most profitable —and the hardest to identify— links.

6.3 Assessing the strategic response of bureaucrats to the reform

6.3.1 The response of top bureaucrats

How did public sector managers and advisors respond to the policy change? To answer this question, I estimate the differential impact that family connections to top bureaucrats had after the introduction of the law. In particular, I estimate the following econometric specification:

$$(11) \quad E_{i,t} = \theta_i + \delta_t + \gamma_k + \eta_1 \cdot B_{f,k,t}^{top} + \eta_2 \cdot [\mathbf{1}(t \geq 2015-II) \times B_{f,k,t}^{top}] + \mathbf{X}_{it}'\Phi + \xi_{i,t},$$

where the notation is the same as in Equation 4. The outcome variables are again the log of total earnings and the indicator of hierarchical promotion. The coefficient of interest is η_2 and captures the differential return of family connections to top bureaucrats following the reform. Since this policy directly affected the appointment and promotion of family members, one would expect a reduction in the likelihood of being hierarchically promoted when connected to a top bureaucrat following the reform and a non-effect on total earnings given that those were not contemplated or covered by the law.

Table 9 present the main results. The most demanding specifications in Columns 3 and 6 show that the law reduced the likelihood of being hierarchically promoted by almost 50% with respect to the sample mean, a sizable decrease. However, this reduction was also followed by an increase of about 2% in terms of total earnings for those who became family-connected after the law passed. These results are consistent with top bureaucrats substituting between the two margins of favoritism available to them.

These results are substantially different from what has been found in the closest empirical setting to this paper. For example, in a historical context, (Xu, 2018) finds that after the removal of patronage in the British Empire, the salary gap between socially connected vs. non-connected governors disappears entirely once the Warren Fisher reform was enacted. In contrast, I find that top bureaucrats strategically respond to the new anti-nepotism legislation reacting only to the restricted type of appointments.

6.3.2 The response of middle-tier and lower-tier bureaucrats

How did other bureaucrats involved in nepotistic connections respond to the policy change? To answer this question, I restrict my analysis to only non-top bureaucrats who were po-

⁵⁷Effects at one degree of consanguinity = $-24.31/55.41 \approx 43.8\%$, Effect at two degrees of consanguinity = $-15.25/95.31 \approx 16\%$.

tentially involved in an illegal connection one period before the law was enacted. Therefore, I consider middle-tier and lower-tier bureaucrats connected to a top bureaucrat at four degrees of consanguinity or less in the same institution they were working on by the first half of 2015.

Using this sample, I follow these individuals over time through three mutually exclusive states: “illegal,” “legal,” or “out”. The first state “illegal” is reached if bureaucrats stay put or become connected to another top bureaucrat at four degrees of consanguinity or less in subsequent periods. In contrast, the “Legal” status is reached when bureaucrats move to another public sector agency where no family connection to a top bureaucrat exists at such degrees. Finally, bureaucrats get to the “Out” state when they leave public administration by either moving to the private sector or becoming unemployed.

Figure 10 shows the result of this tracing exercise. Both panels show in hollow bars the fraction (i.e., the stock) of bureaucrats at each state starting from the first half of 2015 to the second half of 2017. In colors, I present the flows of bureaucrats from one state to another over time.⁵⁸ Panel A presents in red the paths of those bureaucrats who were part of a potentially illegal connection before the law was enacted and remain at the same state in the semester the law was passed. Similarly, Panel B shows the paths of those who shifted to the “Legal” state in the semester that the law was enacted. Appendix Figure A-13 shows the same Figure for those who leave the public administration.

There are two main takeaways from Figure 10. First, 40% of bureaucrats are entirely unresponsive to the reform, and just 13% abide by the law and leave the public administration after two years. Second, more than 30% of these potentially illegal bureaucrats reshuffle within the public administration, while the recidivism rate is about 10% every period. Overall, these results imply that the law was ineffective in purging the administration from these connections and is consistent with anecdotal evidence pointing out the difficulty of eradicating this behavior within public administrations.

7 Conclusions

Bureaucratic nepotism is one of the most chronic pathologies within public administrations around the world. Yet, the lack of comprehensive data and suitable empirical settings have limited its measurement and understanding in modern bureaucracies.

By collecting and combing confidential information on bureaucrats’ family ties and employer-employee records on the universe of civil servants in Colombia (2011-2017), this paper provides the first systematic empirical examination of bureaucratic nepotism and anti-nepotism legislation in an entire modern bureaucracy.

My results suggest that family networks, in general, and family connections to public sector managers and advisors, in particular, can severely distort the promotion, compensation, and performance of workers in the public administration. I show that not only close family ties are negatively related to the performance of governmental agencies and individ-

⁵⁸Appendix Table A-9 presents the underlying data and transition matrices used to generate this figure.

ual bureaucrats, but that workers that become family-connected to top bureaucrats end up receiving significantly higher salaries and promotion prospects. However, since promotion and compensations in the public sector are usually determined by rigid pay grades, I argue that these effects are driven mainly by the allocation of family members to higher remunerated contracts, the temporary promotion of workers to leadership positions, and through the temporary filling of vacancies that are in the process of being assigned via meritocratic examinations.

More importantly, I show that all these estimated private benefits occur at the cost of promoting a worse set of workers in terms of public sector experience, education, and records of misconduct, i.e., directly affecting the administrative capacity of the state.

When analyzing the introduction of the anti-nepotism legislation of 2015, I show that these distortions are difficult to overcome since it is i) challenging to identify distant family connections and ii) workers can strategically respond to these reforms. The latter since this type of legislation could not cover all potential margins of favoritism available to managers and supervisors.

These findings have important implications and inform the debate of public sector reforms aimed to stop the spread of nepotism and other forms of corruption within public administrations.

First, while anti-nepotism legislation has been extensively implemented in most countries, the efforts to improve the monitoring and enforcement of these laws are usually inadequate. This makes identifying the problem difficult over time and extremely challenging to overcome, especially in developing countries where state capacity is already low. My results point to the need for more systematic ways of identifying conflict of interest based on administrative data and automated systems of transparency and enforcement. My empirical methodology provides a starting point for this improved way of detection using already collected data by most governments in Latin America.

Second, my results speak to the already documented problem of temporal contracts and temporal positions in the public sector. These positions have been shown not just to be used by politicians to reward political supporters (Colonnelli et al., 2020) but also, as my results and others recently suggest (Brassiolo et al., 2021), by top non-elected bureaucrats to extract rents for their family members. Redirecting the attention to limit direct and temporary contracts, thus, constitutes an essential step towards the fight against corruption in developing countries.

Finally, the overall emphasis on political nepotism rather than on bureaucratic nepotism has limited the actual fight against nepotism in general in the public sector. In this regard, my results also complement recent works shedding light on the importance and influence of public sector managers and other senior bureaucrats in influencing public employment outcomes and public sector performance (Rasul & Rogger, 2018; Fenizia, 2021). However, my results show that context and opportunity determine the ultimate effects of discretionary appointments involving family members. Where state capacity is already low,

allowing for discretionary decisions by public sector managers is detrimental for the performance of the state and its administrative capabilities, which contrasts with what others have found and propose in more capable states (Fenizia, 2021).

While the design of optimal forms of monitoring and enforcement of anti-nepotism legislation is outside the scope of this paper, it is a fruitful avenue of future research.

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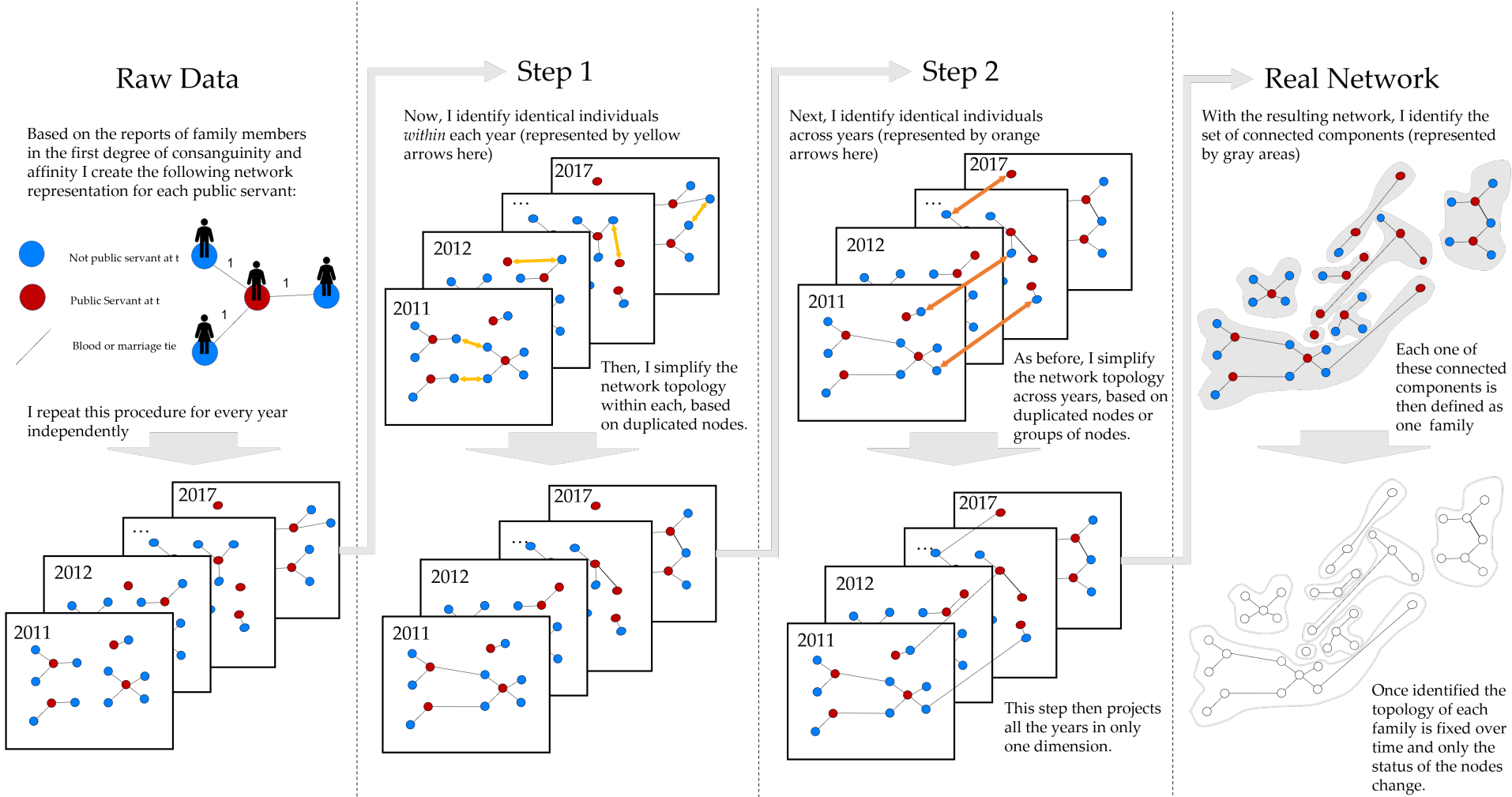
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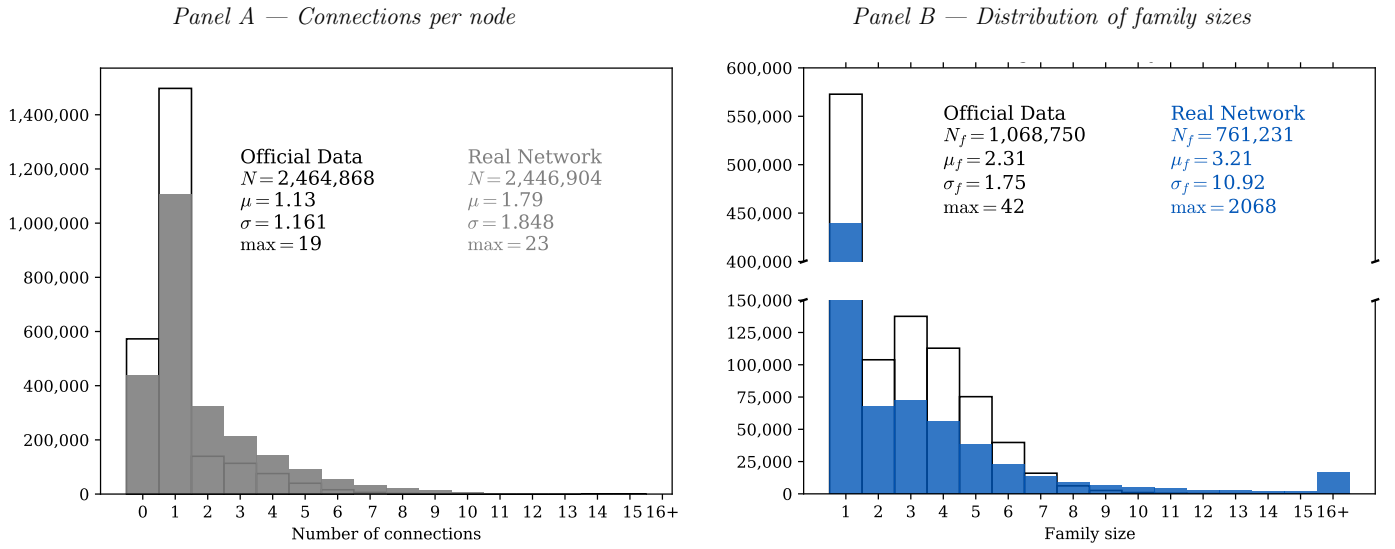
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Figure 1: Family network reconstruction



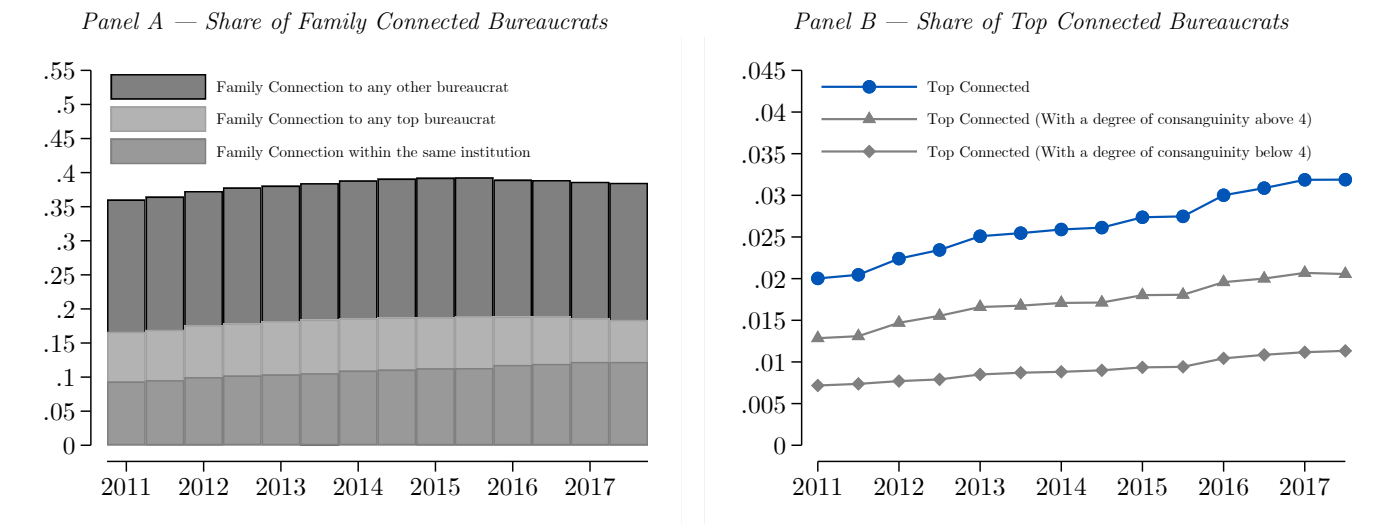
Notes: This figure represents a schematic diagram with the steps followed to convert the reports of family ties to the ultimate network topologies of the families used in the empirical strategy. The number of connections recovered in each step are presented in Table 2.

Figure 2: Distribution of family connections and family sizes before and after the second step of the family network reconstruction



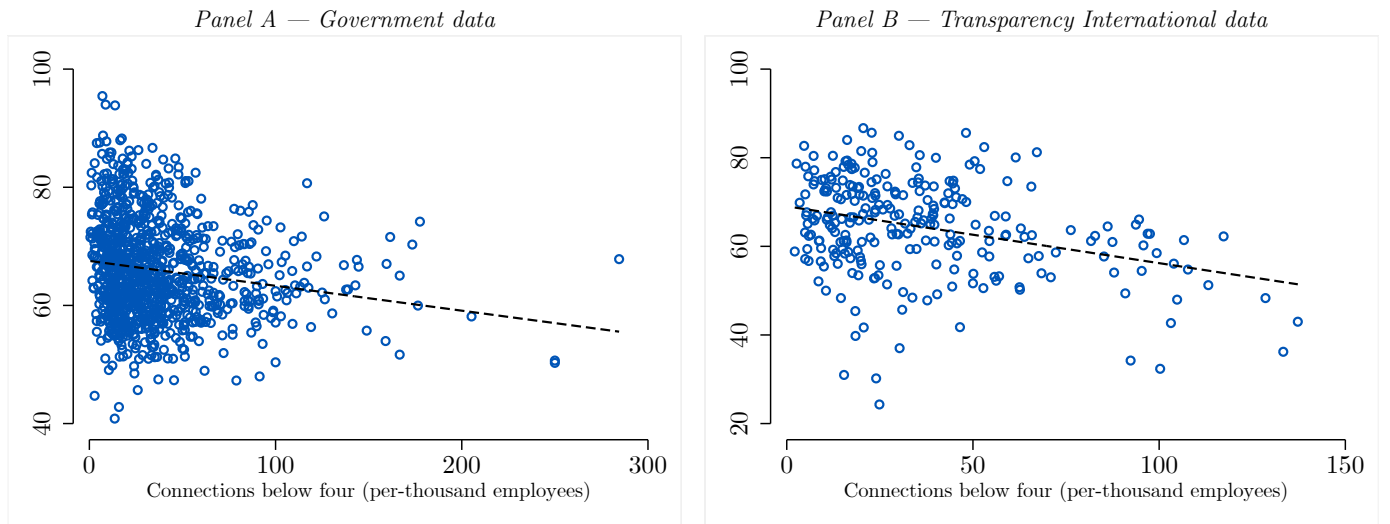
Notes: Panel A displays the distribution and summary statistics of the number of connections per node within families using the raw official data (hollow histogram) and after the reconstruction of the real family network (gray histogram). Panel B displays the distribution and summary statistics of the family sizes (number of members per family) using the raw official data (hollow histogram) and after the reconstruction of the family network (blue histogram).

Figure 3: Shares of family connected bureaucrats within the public administration



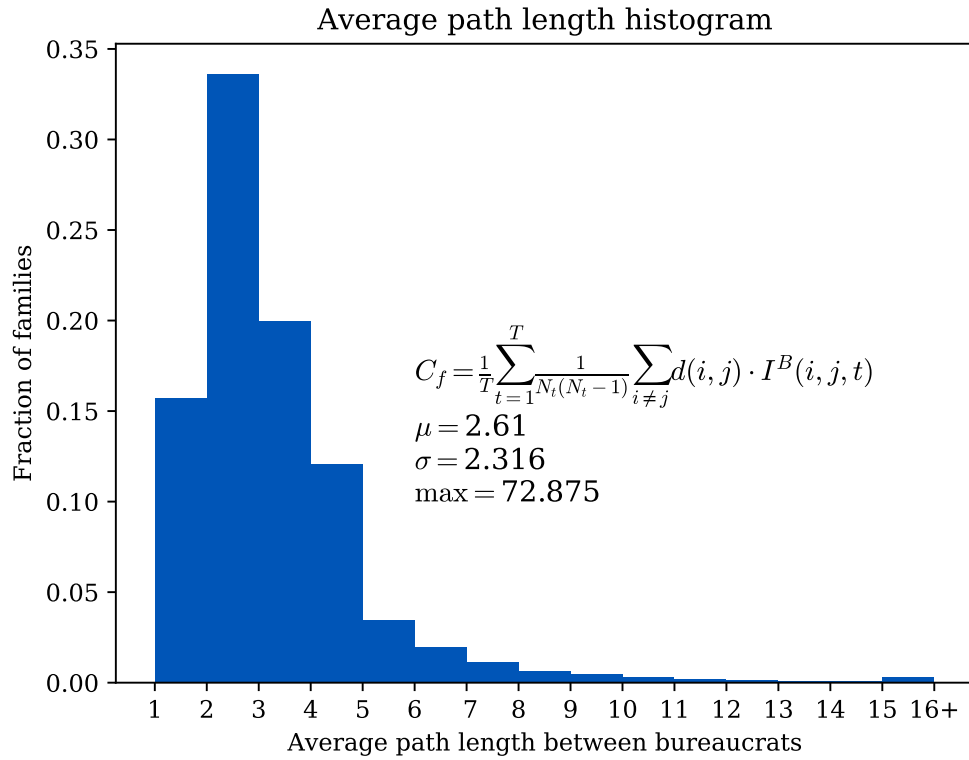
Notes: Panel A presents the share of bureaucrats with family connections to any other bureaucrat, to a top bureaucrat (i.e., manager or advisor), and to any other bureaucrat within the same institution. Panel B presents the share of Top Connected bureaucrats, i.e., the share of bureaucrats with a family connection to a manager or advisor within the same agency they work in. It differentiates the share depending on whether the connections are above or below four degrees of consanguinity.

Figure 4: Close family ties and agency performance



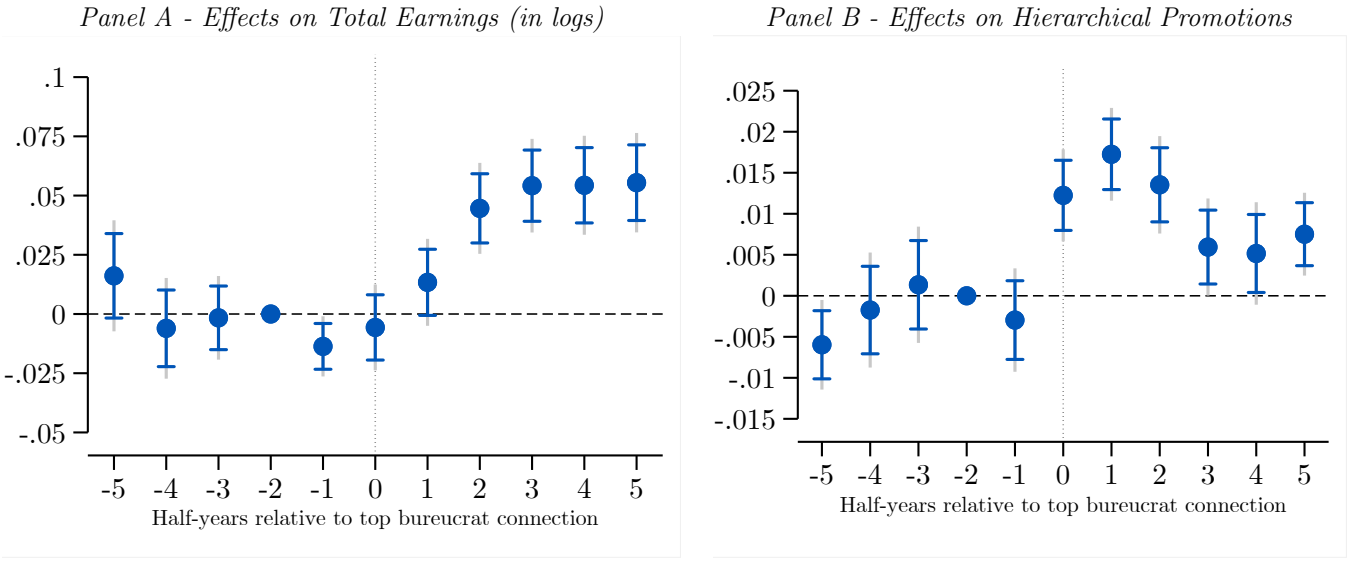
Notes: This figure presents the scatter plot and linear fit between the number of family connections below four degrees of consanguinity and the overall performance index of public sector agencies in 2016 according to government data (Panel A) and the independent assessment from Transparency International (Panel B). The corresponding regressions with further controls are reported in Table 3.

Figure 5: Average degree of consanguinity between bureaucrats across families



Notes: This figure displays the distribution and summary statistics across families of the average path length (in terms of degrees of consanguinity) between family members working in the public administration at the same time. The average path length for each family C_f is computed using the formula displayed in the figure. $I^B(i, j, t)$ is an indicator variable equal to one if individuals i and j from family f are working in the public administration at time t ; $d(i, j)$ is the degree of separation between them in terms of consanguinity degrees, and N_t is the total number of bureaucrats from family f at t .

Figure 6: Effects of having a family connection to a public sector manager or advisor



Notes: Figure displays the coefficients and 99% and 95% confidence intervals from the event-study of ever getting a family connection to a top bureaucrat (i.e., to a public sector manager or advisor) when looking at total earnings and hierarchical promotions as outcomes. These coefficients correspond to η parameters in the following econometric specification, where i indexes individuals, k agencies, f families, and t time periods.

$$E_{i,t} = \theta_i + \delta_t + \gamma_{k(i,t)} + \eta_5 \sum_{\ell \leq -5} B_{f,k,\ell}^{top} + \sum_{\ell = -4, \ell \neq 2}^4 \eta_\ell \cdot B_{f,k,\ell}^{top} + \eta_5 \sum_{\ell \geq 5} B_{f,k,\ell}^{top} + \mathbf{X}_{i,t}' \boldsymbol{\Phi} + \xi_{i,t}$$

Standard errors are clustered at the dyadic family-agency level. The reference period is the year before the first family connection to a top bureaucrat (-2 half-years in the graph). Each figure is based on 6,390,117 panel observations coming from 722,366 bureaucrats and 34,887 connection events to top bureaucrats.

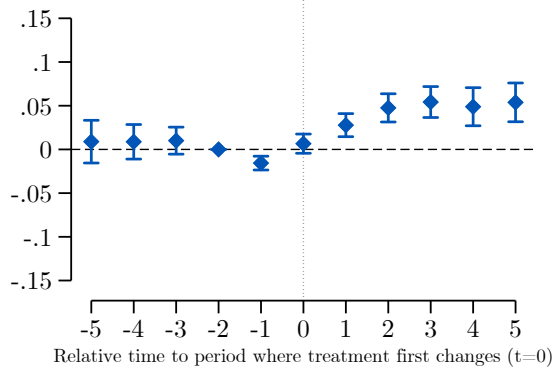
Figure 7: Effects of having, winning, or losing a family connection to a top bureaucrat, corrected by treatment heterogeneity

Panel A – Difference-in-Differences estimates of having a family connection on total earnings

$DID_M = 0.0233 (0.0074)^{***}$ based on 95,758 switcher events

Panel B — Winning a connection

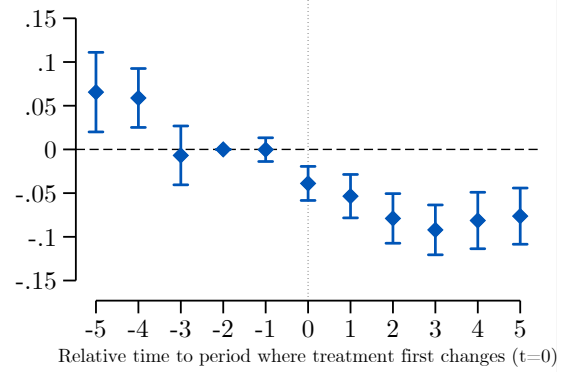
DID_ℓ estimates based on 67,222 switcher events.



Average dynamic effect = $0.0597(0.0095)^{***}$

Panel C — Losing a connection

DID_ℓ estimates based on 28,536 switcher events.



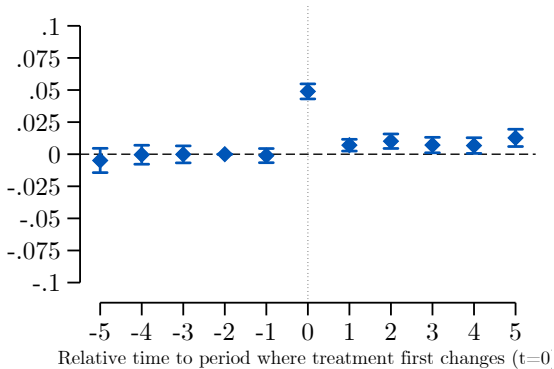
Average dynamic effect = $-0.0858 (0.0144)^{***}$

Panel D – Difference-in-Differences estimates of having a family connection on hierarchical promotions

$DID_M = 0.0121 (0.0023)^{***}$ based on 95,758 switcher events

Panel E — Winning a connection

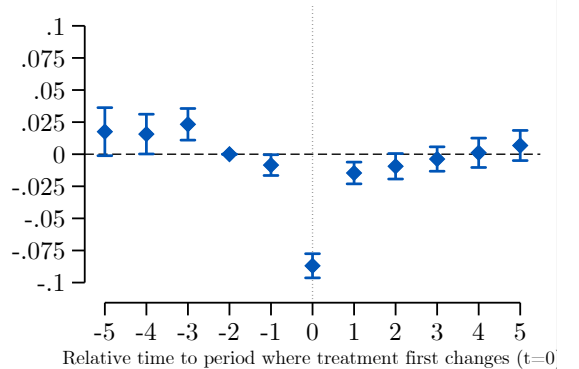
DID_ℓ estimates based on 67,222 switcher events.



Average dynamic effect = $0.0258(0.0028)^{***}$

Panel F — Losing a connection

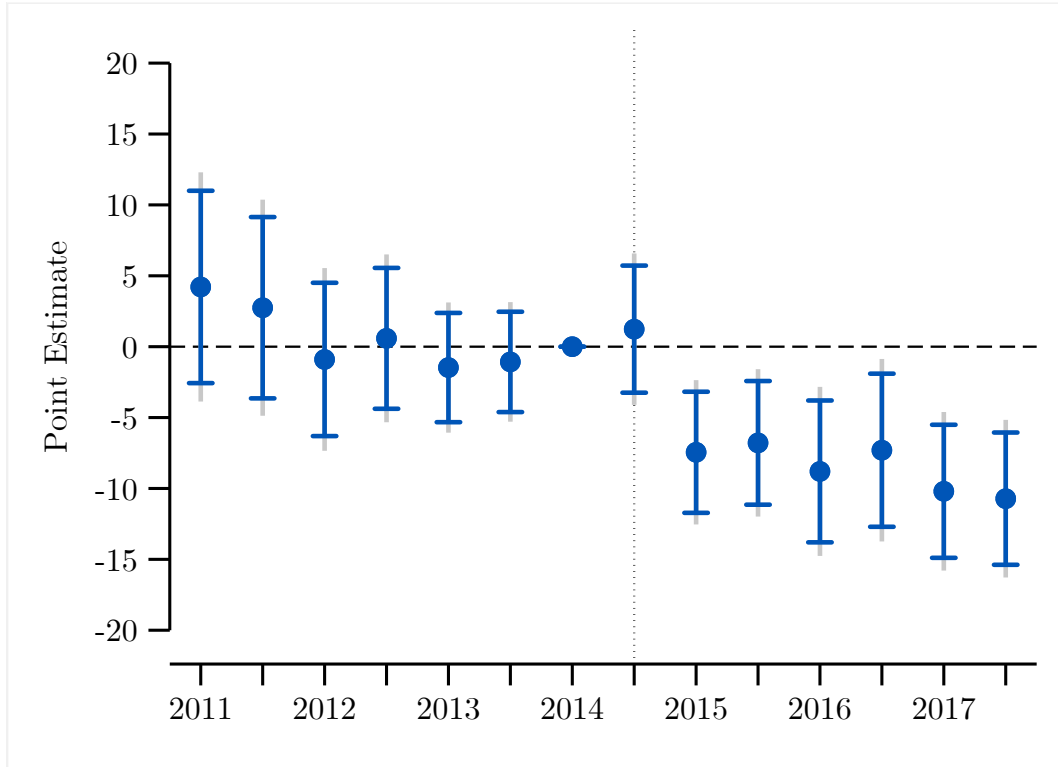
DID_ℓ estimates based on 28,536 switcher events.



Average dynamic effect = $-0.0274(0.0047)^{***}$

Notes: Figure displays the coefficients from the event study of getting a family connection to a top bureaucrat (i.e., to a top manager or advisor) when looking at the log of total earnings as outcome. These coefficients correspond to the ones proposed by [de Chaisemartin and D'Haultfœuille \(2020, 2021\)](#)

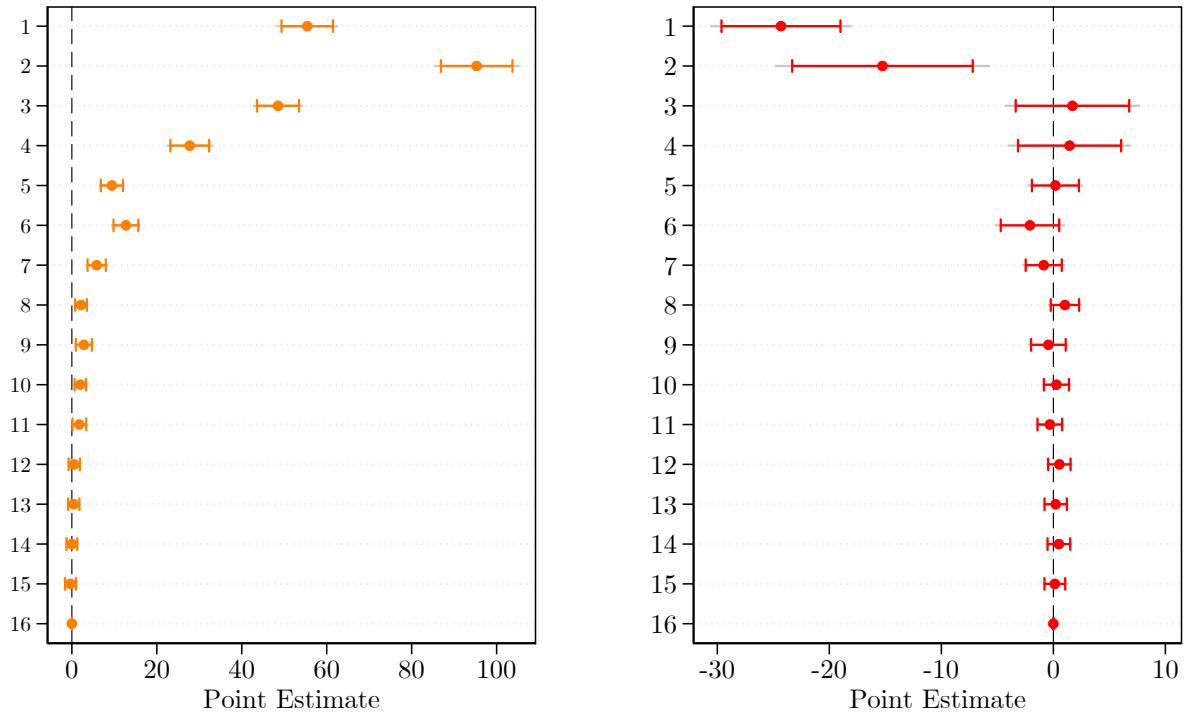
Figure 8: Effects of the 2015 anti-nepotism reform on illegal connections



Notes: Figure presents the point estimates and 95% and 90% confidence intervals corresponding to the coefficients β_τ in equation $N_{skt} = \sum_{\tau=2011-I}^{2017-II} \beta_\tau \cdot [\mathbf{1}(t = \tau) \times \mathbf{1}(s \leq 4)] + \lambda_s + \gamma_{kt} + \xi_{skt}$. The reference period is the first semester of 2014.

Figure 9: Effects of the 2015 anti-nepotism reform by degrees of consanguinity

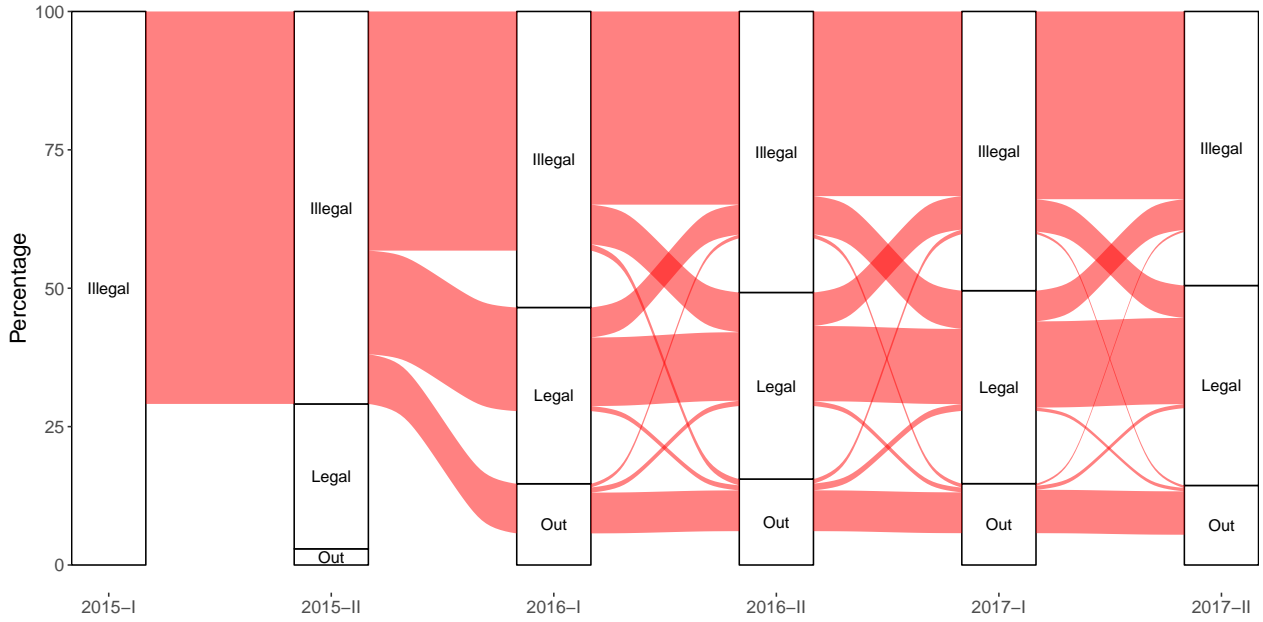
Average number of family connections (λ_ϕ) Change in family connections post reform (β_ϕ)



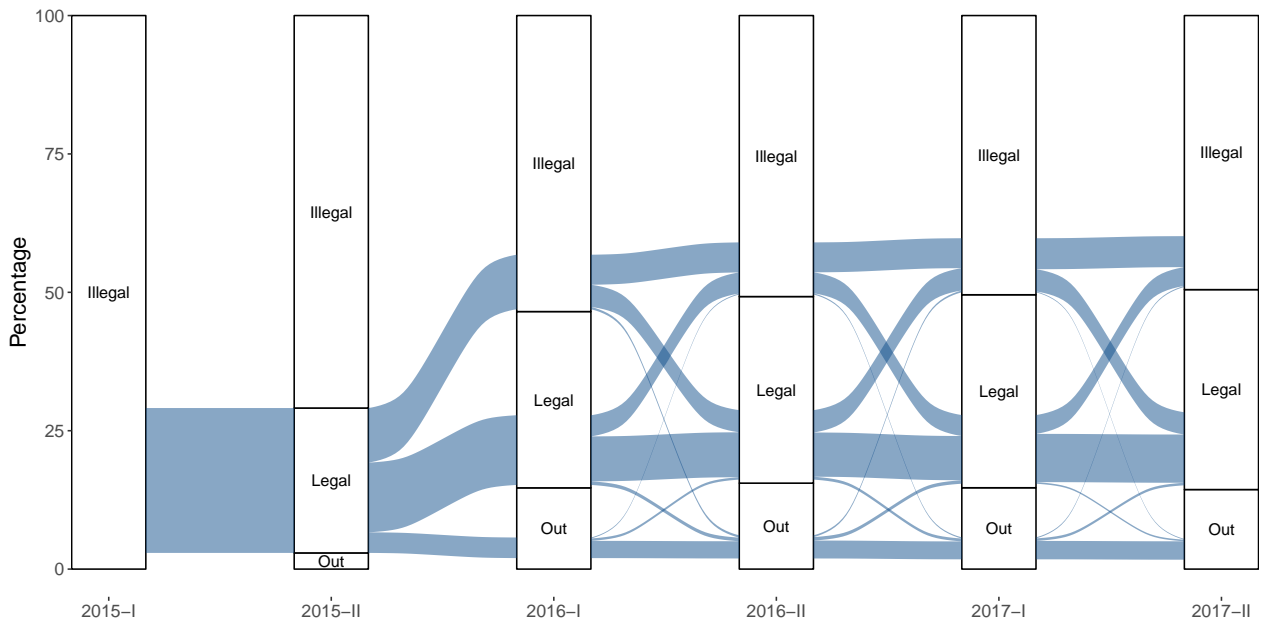
Notes: Figure presents the point estimates and 95% and 90% confidence intervals corresponding to the coefficients λ_ϕ and β_ϕ in the following econometric specification: $N_{skt} = \sum_{\phi=1}^{15} \lambda_\phi \cdot \mathbb{1}(s = \phi) + \sum_{\phi=1}^{15} \beta_\phi \cdot [\mathbb{1}(t \geq 2015-I) \times \mathbb{1}(s = \phi)] + \gamma_{kt} + \xi_{skt}$. The reference category are family connections at 16 or more degrees of separation or more.

Figure 10: Recidivism and reshuffling within the public administration

Panel A: Paths of those who remain in an illegal connection at 2015-II



Panel B: Paths of those who become legal at 2015-II



Notes: This figure shows the shares and flows over time of middle- and lower-tier bureaucrats who were part of an illegal connection in the first semester of 2015-I. Using this sample, the figure follows bureaucrats over time through three mutually exclusive states: “illegal,” “legal,” or “out”. The first state “illegal” is reached if bureaucrats stay put or become connected to another top bureaucrat at four degrees of consanguinity or less in the next period. In contrast, the “Legal” status is reached when bureaucrats move to another public sector agency where not family connection to a top bureaucrat exists at such degrees. Finally, bureaucrats get to the “Out” state when they leave the public administration by either moving to the private sector or unemployment. Both panels show in hollow bars the fraction (i.e., the stock) of bureaucrats at each state labeled in the column. In colors, the figure presents flows of bureaucrats from one state to another. Appendix Table A-9 presents the underlying data with the transition matrices used to generate this figure. Panel A presents in red the paths of those bureaucrats who were part of an illegal connection before the anti-nepotism reform was enacted and remain at the same state in the semester in which the law was passed 2015-II. Similarly, Panel B shows the paths of those who shifted to the “Legal” state in the semester in 2015-II. Appendix Figure A-13 shows the same table for those who “leave” the public administration in 2015-II.

Table 1: Descriptive statistics at the individual-time level

Variables	Mean	SD	Min	Max	Observations
<i>Panel A - Full panel</i>					
Wage (inverse hyperbolic sine of the wage)	7.165	3.806	0	13.641	11,524,713
Public sector experience (half-years)	10.613	15.823	0	116	11,524,713
Private sector experience (half-years)	5.264	8.335	0	104	11,524,713
Public sector employment	0.559	0.497	0	1	11,524,713
Enters into the public sector	0.057	0.232	0	1	11,524,713
Exits from the public sector	0.030	0.170	0	1	11,524,713
Has a family connection to...					
- any bureaucrat	0.353	0.478	0	1	11,524,713
- a top bureaucrat	0.166	0.372	0	1	11,524,713
<i>Panel B - Private sector observations</i>					
Total earnings (inverse hyperbolic sine)	4.557	4.412	0	13.278	5,082,626
Public sector experience (half-years)	1.94	5.287	0	91	5,082,626
Private sector experience (half-years)	6.295	8.789	0	104	5,082,626
Has a family connection to...					
- any bureaucrat	0.314	0.464	0	1	5,082,626
- a top bureaucrat	0.143	0.35	0	1	5,082,626
<i>Panel C - Public Sector observations</i>					
Total earnings (inverse hyperbolic sine)	9.224	0.975	0.002	13.641	6,442,086
Promoted	0.033	0.179	0	1	6,442,086
Public sector experience (half-years)	17.455	17.879	1	116	6,442,086
Private sector experience (half-years)	4.45	7.863	0	103	6,442,086
Hierarchical position is...					
- professional	0.293	0.455	0	1	6,442,086
- technician	0.092	0.289	0	1	6,442,086
- clerical	0.188	0.391	0	1	6,442,086
- contractor	0.427	0.495	0	1	6,442,086
Has a family connection to...					
- any bureaucrat	0.384	0.486	0	1	6,442,086
- a top bureaucrat	0.184	0.387	0	1	6,442,086
- any bureaucrat in the same agency	0.111	0.314	0	1	6,442,086
- a top bureaucrat in the same agency	0.027	0.162	0	1	6,442,086
≡ Top Connected					

Notes: Observations at the bureaucrat×half-year level. Panel includes all bureaucrats that never become top managers or advisors, $n_{ntop} = 824,320$.

Table 2: Family network reconstruction
Distribution of edges before and after family reconstruction algorithm

	Distribution of edges in the raw data	Distribution of edges uncovered in...		Distribution of edges in the Real Network
		Step 1	Step 2	
		(1)	(2)	
<i>Type of family connection</i>				
Ever-bureaucrat — Ever-bureaucrat	3.25%	30.32%	26.48%	12.08%
Ever-bureaucrat — Relative never bureaucrat	96.75%	69.42%	73.52%	87.92%
Total edges uncovered	-	28,343	796,349	-
Total edges	1,397,096	-	-	2,191,264

Notes: This table presents the distribution of family linkages depending on the link type before and after the family network reconstruction algorithm. The distribution for the raw data is presented in Column 1, and for the Real Network (reconstructed data) in Column 4. Columns 2 and 3 show the percentage of connections uncovered in each step of the algorithm. Ever-bureaucrat refers to individuals who are or become bureaucrats at some point between 2011 to 2017. Details about the two steps used in the reconstruction of family networks are described in Section 3.2. The total number of edges in Column 4 does not include 30,524 perfect deduplications corrected during steps 1 and 2. Total linkages uncovered: 824,692. Total Ever-bureaucrat to Ever-bureaucrat linkages recovered: 219,478.

Table 3: Agency performance and the presence of close family connections*Panel A: Agency level performance based on Government data*

Dependent variable:	Agency performance index based on Government data					
	(1)	(2)	(3)	(4)	(5)	(6)
Share of connections below four degrees of consanguinity	-0.0728*** (0.0120)	-0.0678*** (0.0122)	-0.0225* (0.0122)	-0.0838*** (0.0128)	-0.0469*** (0.0124)	-0.0356*** (0.0124)
<i>Fixed effects</i>						
- Degree of centralization		Yes				Yes
- Administrative level			Yes			Yes
- Branch of the government				Yes		Yes
- Type of agency (legal nature)					Yes	Yes
Observations	3,853	3,853	3,853	3,853	3,853	3,853
R-squared	0.2183	0.2206	0.2765	0.2677	0.3552	0.3747

Panel B: Agency level performance based on Transparency International data

Dependent variable:	Agency performance index based on Transparency International data					
	(1)	(2)	(3)	(4)	(5)	(6)
Share of connections below four degrees of consanguinity	-0.2902*** (0.0564)	-0.3017*** (0.0579)	-0.2257*** (0.0612)	-0.3181*** (0.0556)	-0.2384*** (0.0803)	-0.2377*** (0.0834)
<i>Fixed effects</i>						
- Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
- Degree of centralization		Yes				Yes
- Administrative level			Yes			Yes
- Branch of the government				Yes		Yes
- Type of agency (legal nature)					Yes	Yes
Observations	419	419	419	419	419	419
Agencies	251	251	251	251	251	251
R-squared	0.1733	0.1802	0.1879	0.2153	0.2755	0.2994

Notes Panel A: Observations are at the agency level. Sample includes all Public Sector agencies included in the *Medicion del desempeno Institucional* (MDI) database in 2016. Share of connections below four refers to the number of family connections below four degrees of consanguinity per one thousand employees within the agency. All columns control for the total number of employees in each year and the number of family connections below four degrees of consanguinity. The table reports the standardized (beta) coefficients, i.e., dependent and independent variables were standardized before estimating the regressions. Robust standard errors in parentheses.

Notes Panel B: Observations are at the agency-year level. Sample includes all public sector agencies included in the Transparency Index of Public Entities (ITEP) in 2014 and 2016. Share of connections below four refers to the number of family connections below four degrees of consanguinity per one thousand employees within the agency. All columns control for the total number of employees in each year and the number of family connections below four degrees of consanguinity. The table reports the standardized (beta) coefficients, i.e., dependent and independent variables were standardized before estimating the regressions. Robust standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Labor market returns to family ties to top-bureaucrats in the public sector

Dependent variable:	Total Earnings (logs)			Worker is Hierarchically Promoted		
	(1)	(2)	(3)	(4)	(5)	(6)
Mean dependent variable	9.22	9.22	9.22	0.033	0.033	0.033
Top Connected	0.03740*** (0.00579)	0.03032*** (0.00576)	0.03047*** (0.00565)	0.01468*** (0.00105)	0.01437*** (0.00105)	0.01345*** (0.00105)
<i>Time varying controls</i>						
<i>by levels of education</i>						
- Private Experience	-	Yes	Yes	-	Yes	Yes
- Public Experience	-	Yes	Yes	-	Yes	Yes
<i>Fixed effects</i>						
- Bureaucrat fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
- Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
- Agency fixed effects	-	-	Yes	-	-	Yes
Observations	6,390,201	6,390,201	6,390,117	6,390,201	6,390,201	6,390,117
Bureaucrats	722,375	722,375	722,366	722,375	722,375	722,366
R-squared	0.73122	0.73208	0.74049	0.10877	0.10887	0.11358

Notes: The unit of observation is bureaucrat-time. Sample includes just bureaucrats within the public sector. Top connected is a dummy variable equal to one if the bureaucrat has had a family connection to a manager or advisor within the governmental agency he/she is working in. Sample includes all serving bureaucrats from 2011 to 2017. Promotion dummy refers to an upward change within the hierarchy of the institution. Total earnings refers to inverse hyperbolic sine of the wage in thousand Colombian pesos. 51,969 singleton observations dropped. Private and Public Experience varying by level of education l are included as follows $\sum_{l \in E} \text{experience} \times \mathbb{1}(\text{education} = l)$. Standard errors clustered at the dyadic family-agency level in parentheses. *** $p < 0.01$.

**Table 5: Labor market returns to family ties to top-bureaucrats in the public sector:
Ruling out family-specific and agency-specific common shocks**

Dependent variable:	Total Earnings (log)			Worker is hierarchically Promoted		
	(1)	(2)	(3)	(4)	(5)	(6)
Mean dependent variable	9.22	9.22	9.22	0.033	0.033	0.033
Top Connected	0.03047*** (0.00565)	0.02593*** (0.00533)	0.03297*** (0.01270)	0.01345*** (0.00105)	0.00957*** (0.00103)	0.02075*** (0.00237)
<i>Time varying controls</i>						
<i>by levels of education</i>						
- Private experience	Yes	Yes	Yes	Yes	Yes	Yes
- Public experience	Yes	Yes	Yes	Yes	Yes	Yes
<i>Fixed effects</i>						
- Bureaucrat fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
- Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
- Agency fixed effects	Yes			Yes		
- Agency × Time fixed effects		Yes			Yes	
- Family × Time fixed effects			Yes			Yes
Observations	6,390,117	6,390,117	6,390,117	6,390,117	6,390,117	6,390,117
Bureaucrats	722,375	722,375	722,366	722,375	722,375	722,366
R-squared	0.74049	0.76522	0.93759	0.11358	0.19867	0.76775

Notes: The unit of observation is bureaucrat-time. Sample includes just bureaucrats within the public sector. Top connected is a dummy variable equal to one if the bureaucrat has had a family connection to a manager or advisor within the governmental agency he/she is working in. Sample includes all serving bureaucrats from 2011 to 2017. Promotion dummy refers to an upward change within the hierarchy of the institution. Log of earnings in thousand Colombian pesos. 51,969 singleton observations dropped. Standard errors clustered at the dyadic family-agency level in parentheses. *** p<0.01.

Table 6: Differences in pre-promotion characteristics

Dependent Variable:	Pre-promotion characteristic			
	Misperformance		Qualifications	
	Had a Disciplinary Record	Had an Active Inability Record	Exceeded Education Require- ment	Public Experience Ratio
	(1)	(2)	(3)	(4)
Mean dependent variable	0.297	0.112	0.337	0.721
<i>Panel A: Hierarchical Promotions</i>				
Hierarchically Promoted	−0.06364*** (0.00890)	−0.05112*** (0.00474)	0.00458*** (0.00068)	0.04869*** (0.00098)
Top Connected	−0.08890*** (0.03146)	−0.03226* (0.01810)	0.01662*** (0.00207)	0.02392*** (0.00184)
Hierarchically Promoted × Top Connected	0.08873** (0.04120)	0.05180** (0.02474)	−0.01073*** (0.00302)	−0.00587* (0.00356)
<i>Fixed Effects</i>				
Seniority×Position×Agency×Choice-period	Yes	Yes	Yes	Yes
Pools of Candidates	194,426	194,426	194,426	188,620
Observations	4,906,044	4,906,044	4,906,044	4,818,860
R-squared	0.04264	0.02617	0.68061	0.29577
<i>Panel B: Promotions in terms of Total Earnings</i>				
Promotion in Earnings	−0.10577*** (0.01289)	−0.05551*** (0.00811)	0.00626*** (0.00055)	0.05650*** (0.00060)
Top Connected	−0.08570** (0.03596)	−0.02534 (0.01990)	0.01470*** (0.00205)	0.02414*** (0.00187)
Promotion in Earnings × Top Connected	0.06343* (0.03640)	0.00671 (0.02219)	−0.00273 (0.00175)	−0.01230*** (0.00191)
<i>Fixed Effects</i>				
Seniority×Position×Agency×Choice-period×WageBin	Yes	Yes	Yes	Yes
Corresponding pools of candidates×choice-periods	345,402	345,402	345,402	339,596
Observations	4,668,473	4,668,473	4,668,473	4,581,289
R-squared	0.09548	0.07221	0.70733	0.35931

Notes: The unit of observation is bureaucrat-choice period. All columns include a full set of Seniority×Position×Agency×Choice-period fixed effects. The sample includes all bureaucrats within the public sector for agencies that experience at least one promotion at time t . Top connected is a dummy variable equal to one if the bureaucrat has had a family connection to a manager or advisor within the governmental agency he/she is working in at the choice-period t . Promotion dummy refers to an upward change within the hierarchy of the institution. Dependent variables multiplied by 100, standard errors clustered at the bureaucrat level in parentheses.
*** p<0.01 ** p<0.05.

Table 7: Evaluating the anti-nepotism legislation of 2015

	(1)	(2)	(3)	(4)
Dependent Variable:	Family connections per ten-thousand employees			
Mean dependent variable:	58.01	58.01	58.01	58.01
Illegal \times Post Reform	-9.0522*** (1.8582)	-9.0522*** (1.8115)	-9.0522*** (1.7989)	-9.0522*** (1.8200)
Illegal	53.6483*** (1.9926)	53.6483*** (1.9088)		
Post Reform	0.0308 (0.2029)	2.1223*** (0.3956)		
<i>Fixed effects</i>				
- Agency		Yes	Yes	
- Time			Yes	
- Degree of consanguinity			Yes	Yes
- Agency \times Time				Yes
Institutions	1,351	1,351	1,351	1,351
Observations	180,976	180,976	180,976	180,976
R-squared	0.0742	0.1232	0.1443	0.1540

Notes: Unit of observation is degree of separation-institution-time. The number of family connections excludes family ties at the same hierarchical level. Sample includes all institutions with at least one family connection at any degree of separation between 2011 to 2017. Standard errors clustered at the institution \times degree of separation level in parentheses. *** $p < 0.01$.

Table 8: Anti-nepotism law of 2015: Effects by branches of the government

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	Total family connections per ten-thousand employees				
	Branches of government			Autonomous & Independent	
Institution belongs to:	Executive	Legislative	Judicial	Others	Control & Regulation
Mean dep var pre reform	60.20	25.57	45.65	41.18	40.78
Illegal	56.0534*** (2.1762)	22.5980*** (5.5106)	32.8131*** (10.9587)	35.7671*** (3.5661)	33.8360*** (8.0265)
Illegal \times Post Reform	-10.0303*** (2.0412)	-4.0021 (4.0090)	-15.0945** (7.3605)	1.6905 (2.7664)	-14.8698 (7.8932)
<i>Fixed Effects</i>					
- Institution \times Time	Yes	Yes	Yes	Yes	Yes
Institutions	1,219	3	7	84	38
Observations	160,976	512	960	13,936	4,224
R-squared	0.1361	0.4514	0.5429	0.1749	0.0624

Notes: Unit of observation is degree of consanguinity-institution-time. The number of family connections include all family ties between bureaucrats within same institution at time t , i.e., excludes family ties at the same hierarchical level. Sample includes all institution-time observations with at least one family connection at any degree of separation between 2011 to 2017. Robust standard errors clustered at the institution \times degree of consanguinity level in parentheses. *** $p < 0.01$, ** $p < 0.05$.

Table 9: labor market returns to family connections to top-bureaucrats within the public sector and the anti-nepotism law of 2015

Dependent variable:	Total Earnings (logs)			Worker is Hierarchically Promoted		
	(1)	(2)	(3)	(4)	(5)	(6)
Mean dependent variable	9.22	9.22	9.22	0.033	0.033	0.033
Top Connected	0.02168*** (0.00686)	0.01585** (0.00682)	0.01532** (0.00675)	0.02779*** (0.00142)	0.02742*** (0.00142)	0.02556*** (0.00142)
Top Connected \times Post Reform	0.01982*** (0.00518)	0.01824*** (0.00511)	0.01905*** (0.00509)	-0.01652*** (0.00114)	-0.01646*** (0.00114)	-0.01523*** (0.00114)
<i>Time varying controls</i>						
<i>by levels of education</i>						
- Private Experience	-	Yes	Yes	-	Yes	Yes
- Public Experience	-	Yes	Yes	-	Yes	Yes
<i>Fixed effects</i>						
- Bureaucrat fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
- Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
- Agency fixed effects	-	-	Yes	-	-	Yes
Observations	6,390,201	6,390,201	6,390,117	6,390,201	6,390,201	6,390,117
Bureaucrats	722,375	722,375	722,366	722,375	722,375	722,366
R-squared	0.73122	0.73208	0.74050	0.10883	0.10893	0.11363

Notes: The unit of observation is bureaucrat-time. Sample includes just bureaucrats within the public sector. Top connected is a dummy variable equal to one if the bureaucrat has had a family connection to a manager or advisor within the governmental agency he/she is working on. Sample includes all serving bureaucrats from 2011 to 2017. Promotion dummy refers to an upward change within the hierarchy of the institution. Wage refers to inverse hyperbolic sine of the wage in thousand Colombian pesos. 51,969 singleton observations dropped. Private and Public Experience varying by level of education l are included as follows $\sum_{l \in E} \text{experience} \times \mathbb{1}(\text{education} = l)$. Standard errors clustered at the dyadic family-agency level in parentheses. *** $p < 0.01$.

Online Appendix

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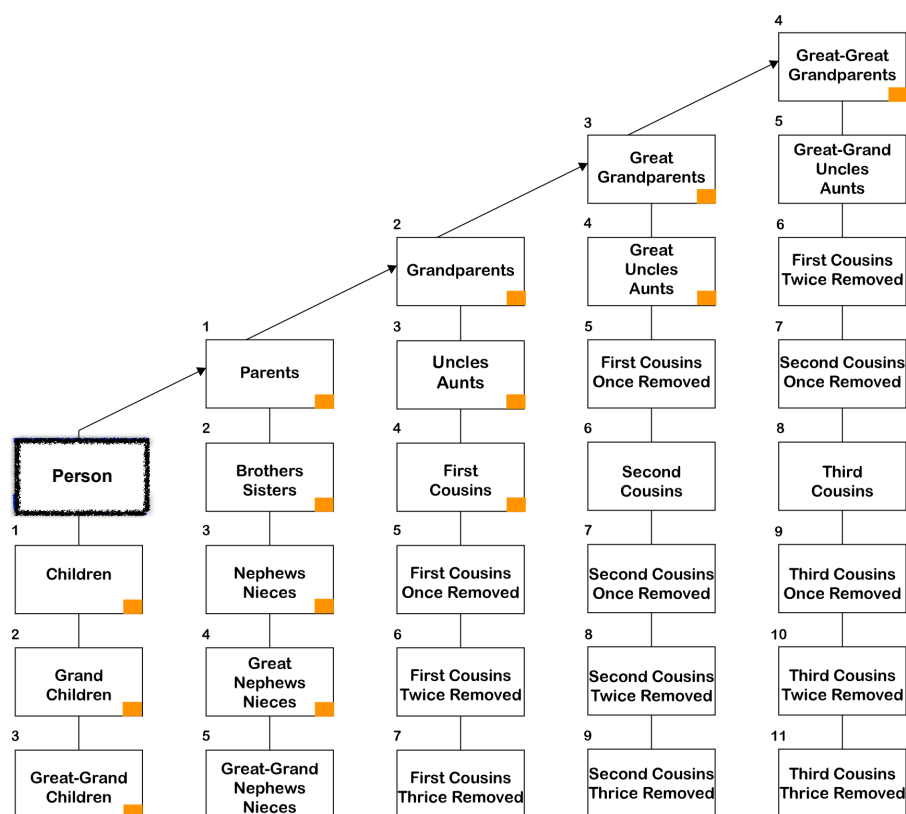
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The scatter plot displays the relationship between Favoritism in decisions of government officials (X-axis) and Government Effectiveness (Y-axis). The X-axis ranges from 1 to 6, and the Y-axis ranges from -2.5 to 2.5. A dashed line indicates a negative correlation. Data points are labeled with country codes.

Country	Favoritism (X)	Government Effectiveness (Y)
SGP	1.1	2.4
FIN	1.3	2.1
CHE	1.6	2.2
NOR	1.4	2.0
SWE	1.5	2.0
NZL	1.2	1.8
ARE	1.1	1.6
DEU	2.1	1.8
DNK	2.2	2.0
LUX	2.3	2.0
JPN	2.4	1.9
AUS	2.5	1.8
IRL	2.6	1.7
GBR	2.7	1.7
USA	2.8	1.8
ISL	2.9	1.7
CAN	3.1	1.8
FRA	3.3	1.6
AUT	3.4	1.6
ESP	3.5	1.5
PRT	3.6	1.5
CHL	3.7	1.4
MYS	2.8	1.3
BEL	3.2	1.3
HRV	3.4	1.3
MUS	3.9	1.1
CYP	4.1	1.2
KOR	4.2	1.4
LTU	4.3	1.4
SVN	4.4	1.4
MLT	4.5	1.3
CZE	4.6	1.2
LVA	4.7	1.3
QAT	1.4	0.8
CHN	2.6	0.6
SAU	2.7	0.5
IND	2.9	0.4
BHR	3.0	0.4
URY	3.1	0.6
BTN	3.2	0.5
OMN	3.3	0.4
JOR	3.5	0.4
AZE	2.8	0.2
GEO	3.8	0.7
ARM	3.9	0.5
CPV	3.9	0.4
THA	4.1	0.5
JAM	4.2	0.7
POL	4.3	0.6
ROU	4.4	0.4
BGR	4.5	0.5
SYC	4.6	0.6
GRC	4.7	0.5
SRB	4.8	0.4
PHL	4.9	0.4
HRV	5.0	0.6
HUN	5.1	0.7
ZAF	5.2	0.6
SVK	5.3	0.8
COL	4.9	0.3
ROU	5.0	0.2
MEX	5.1	0.3
ECU	5.2	0.2
DOM	5.3	0.1
MDA	5.1	-0.2
ISR	4.8	-0.3
IRQ	4.9	-0.4
BHR	5.0	-0.4
IND	5.1	-0.5
NIC	5.2	-0.6
NGA	5.3	-0.7
ZWE	5.4	-0.8
VEN	5.8	-1.2
HTI	5.1	-1.8
YEM	5.0	-2.2
SGP	1.1	2.4
FIN	1.3	2.1
CHE	1.6	2.2
NOR	1.4	2.0
SWE	1.5	2.0
NZL	1.2	1.8
ARE	1.1	1.6
DEU	2.1	1.8
DNK	2.2	2.0
LUX	2.3	2.0
JPN	2.4	1.9
AUS	2.5	1.8
IRL	2.6	1.7
GBR	2.7	1.7
USA	2.8	1.8
ISL	2.9	1.7
CAN	3.1	1.8
FRA	3.3	1.6
AUT	3.4	1.6
ESP	3.5	1.5
PRT	3.6	1.5
CHL	3.7	1.4
MYS	2.8	1.3
BEL	3.2	1.3
HRV	3.4	1.3
MUS	3.9	1.1
CYP	4.1	1.2
KOR	4.2	1.4
LTU	4.3	1.4
SVN	4.4	1.4
MLT	4.5	1.3
CZE	4.6	1.2
LVA	4.7	1.3
QAT	1.4	0.8
CHN	2.6	0.6
SAU	2.7	0.5
IND	2.9	0.4
BHR	3.0	0.4
URY	3.1	0.6
BTN	3.2	0.5
OMN	3.3	0.4
JOR	3.5	0.4
AZE	2.8	0.2
GEO	3.8	0.7
ARM	3.9	0.5
CPV	3.9	0.4
THA	4.1	0.5
JAM	4.2	0.7
POL	4.3	0.6
ROU	4.4	0.4
BGR	4.5	0.5
SYC	4.6	0.6
GRC	4.7	0.5
SRB	4.8	0.4
PHL	4.9	0.4
HRV	5.0	0.6
HUN	5.1	0.7
ZAF	5.2	0.6
SVK	5.3	0.8
COL	4.9	0.3
ROU	5.0	0.2
MEX	5.1	0.3
ECU	5.2	0.2
DOM	5.3	0.1
MDA	5.1	-0.2
ISR	4.8	-0.3
IRQ	4.9	-0.4
B		

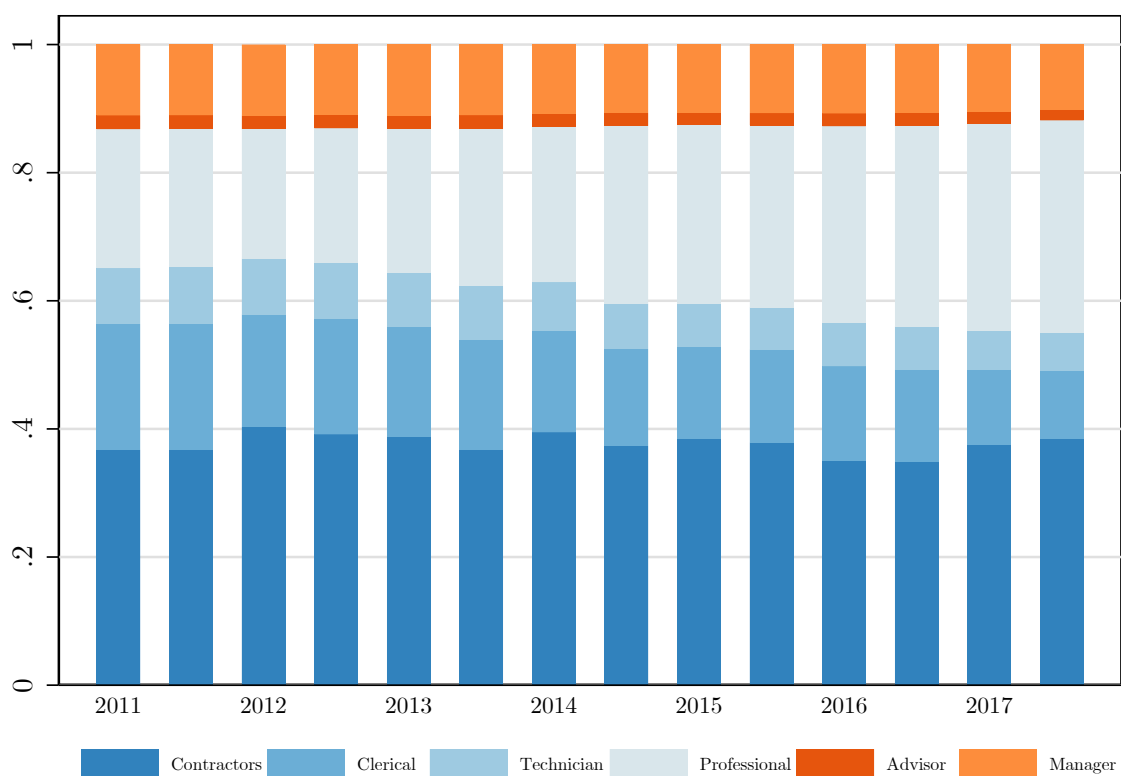
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Figure A-2: Consanguinity degrees and family relationships



Notes: This figure presents a table of consanguinity between different family relationships. The number next to each box indicates the degree of relationship relative to a given person highlighted in the bold box. For example, parents and children of this generic person are at one degree of consanguinity while first cousins and great uncles and aunts are at four. The relationships considered illegal according to the anti-nepotism legislation in Colombia are highlighted in orange. The degree of affinity through spouses is considered the same as the consanguineal level a couple was joined, so that, for example, the degree of affinity of a husband to his sister-in-law is two.

Figure A-3: Hierarchical composition of the public sector over time



Notes: Hierarchical composition of the jobs within the Colombian public sector. It excludes elected officials, military and police forces.

Figure A-4: Public Employment Information System, SIGEP

sigep **REPÚBLICA DE COLOMBIA FUNCIÓN PÚBLICA**

Servidores Públicos Contratistas Entidades Públicas Sigep en cifras

Hojas de Vida

Name1 Name2 Last1 Last2 -----> **Full Name**
Ministro -----> **Position**
MINISTERIO DE RELACIONES EXTERIORES -----> **Institution**

✉ Carlos.Trujillo@cancilleria.gov.co -----> **Contact Information**
 📞 3814000
 📠 3814747
Municipio de Nacimiento: CARTAGO, VALLE DEL CAUCA - COLOMBIA -----> **Place of Birth**

🎓 **Formación Académica** -----> **Academic Background**

- Profesional - DERECHO - Graduado
- Básica secundaria
- Estudio en el Exterior - MASTER OF ARTS DEGREE IN INTERNATIONAL BUSINESS - Graduado

🏢 **Experiencia Laboral** -----> **Professional experience**

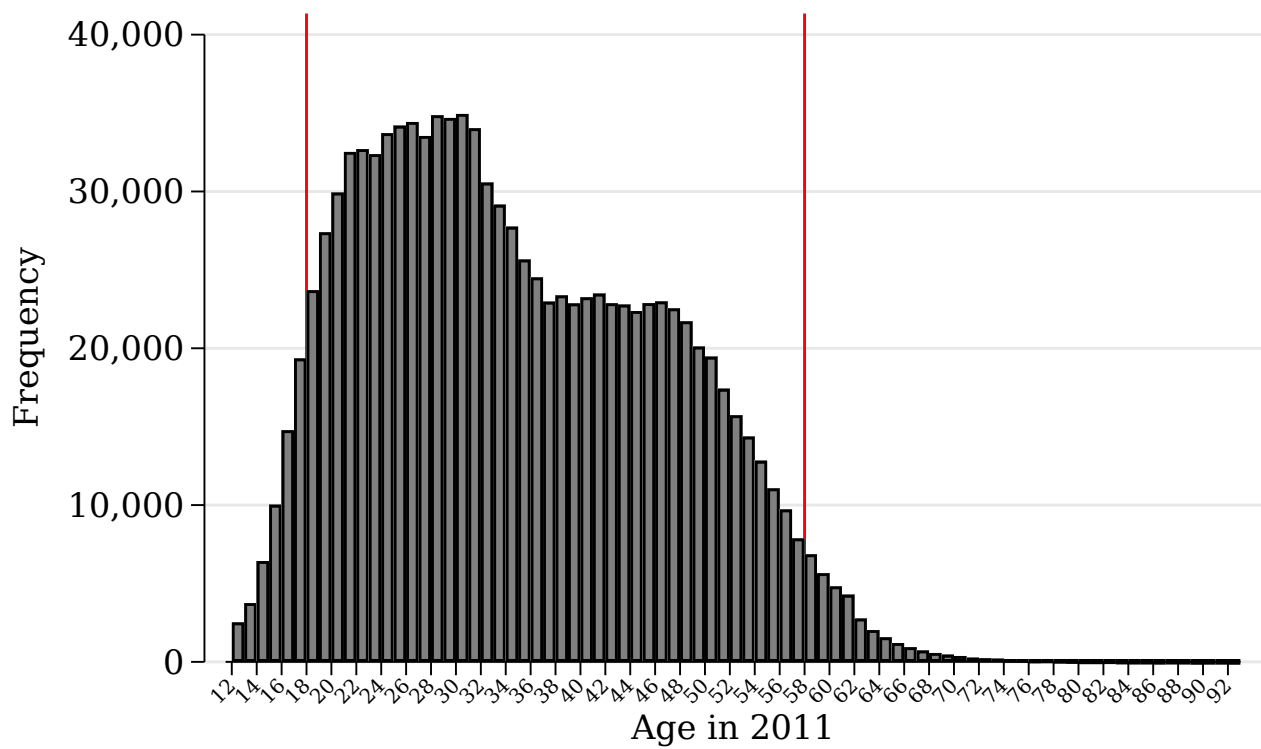
Cargos	Entidad	Fecha Inicio	Fecha Fin
Ministro	MINISTERIO DE RELACIONES EXTERIORES	07/08/2018	Actual
CONTRATISTA	COLEGIO MAYOR DE NUESTRA SEÑORA DEL ROSARIO	01/11/2011	08/08/2018
Embajador Extraordinario Y Plenipotenciario 25	MINISTERIO DE RELACIONES EXTERIORES (EMBAJADA ANTE EL GOBIERNO DE BÉLGICA)	08/02/2006	31/10/2011
Embajador Extraordinario Y Plenipotenciario	MINISTERIO DE RELACIONES EXTERIORES (EMBAJADA ANTE EL GOBIERNO DE SUECIA)	14/05/2004	07/02/2006
DOCENTE	COLEGIO MAYOR DE NUESTRA SEÑORA DEL ROSARIO	20/01/2003	06/06/2003
DOCENTE	COLEGIO MAYOR DE NUESTRA SEÑORA DEL ROSARIO	01/08/2002	18/12/2002
DOCENTE	COLEGIO MAYOR DE NUESTRA SEÑORA DEL ROSARIO	17/01/2002	06/06/2002
DOCENTE	COLEGIO MAYOR DE NUESTRA SEÑORA DEL ROSARIO	01/09/2001	14/12/2001
Embajador Extraordinario Y Plenipotenciario	MINISTERIO DE RELACIONES EXTERIORES (EMBAJADA ANTE EL GOBIERNO DE RUSIA)	19/04/1999	28/02/2001
Embajador Extraordinario Y Plenipotenciario	MINISTERIO DE RELACIONES EXTERIORES (EMBAJADA ANTE EL GOBIERNO DE AUSTRIA)	14/04/1998	18/04/1999
Ministro	MINISTERIO DEL INTERIOR	10/06/1997	27/01/1998
Embajador Extraordinario Y Plenipotenciario	MINISTERIO DE RELACIONES EXTERIORES (ORGANIZACIÓN DE LOS ESTADOS AMERICANOS)	16/10/1996	05/06/1997

Ver Ley de Transparencia y acceso a la información

Job-spell data including position, institution, start date, and end date

Notes: Figure displays an annotated example of the common CV format in the employer-employee database of the Colombian public employment.

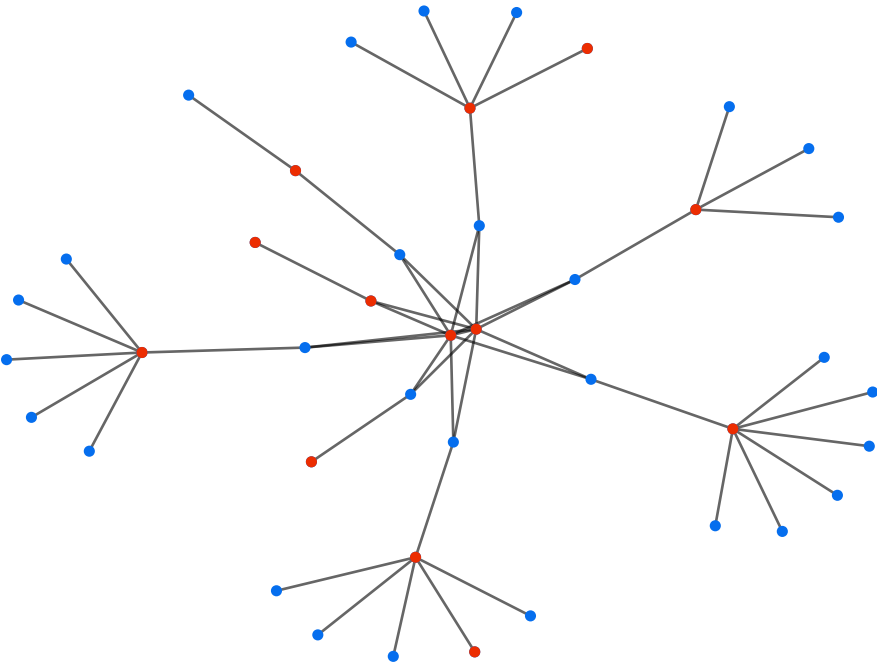
Figure A-6: Age distribution of ever bureaucrats in 2011



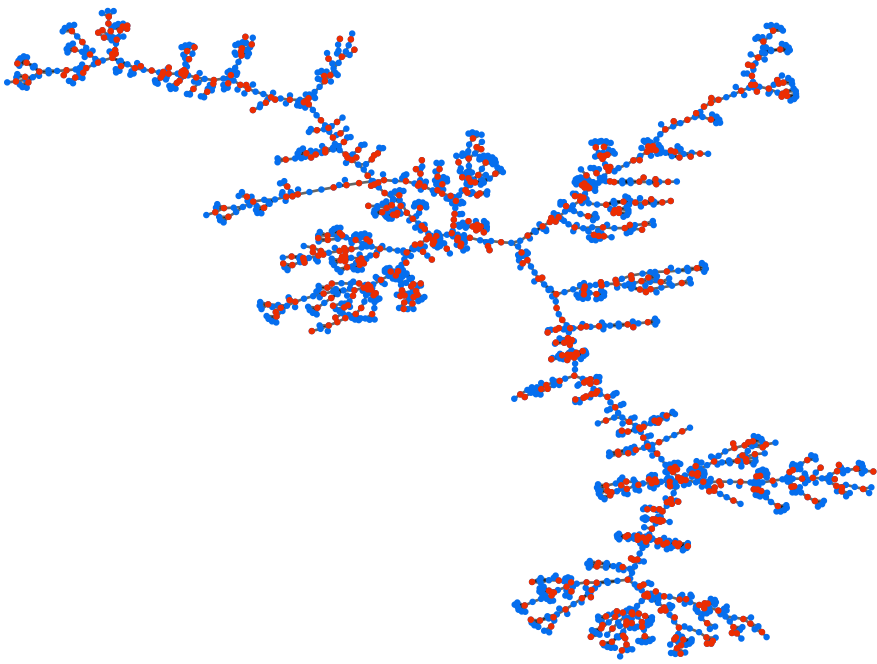
Notes: Figure displays the distribution of ages of ever bureaucrats in 2011. Data between the two red lines (18-59) is the sample used in the baseline specifications.

Figure A-7: Largest family network after each step of the reconstruction algorithm

Official Largest Family Network



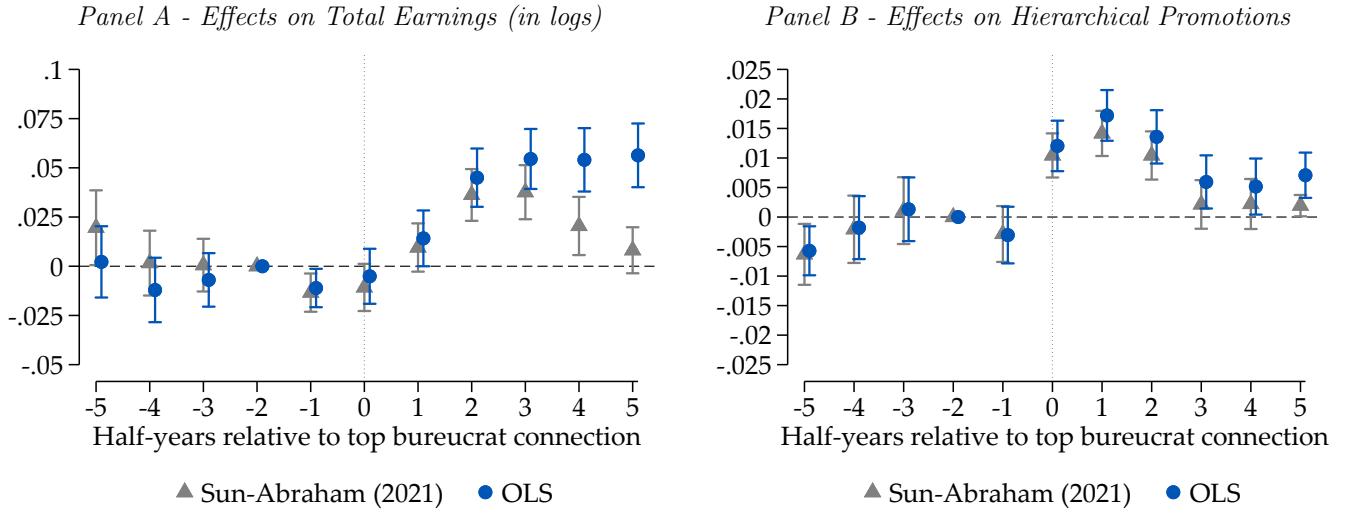
Real Largest Family Network



Panel A - Largest family network topology after Step 1

Panel B - Largest family network topology after Step 2

Figure A-8: Robustness using Sun and Abraham (2020) estimator

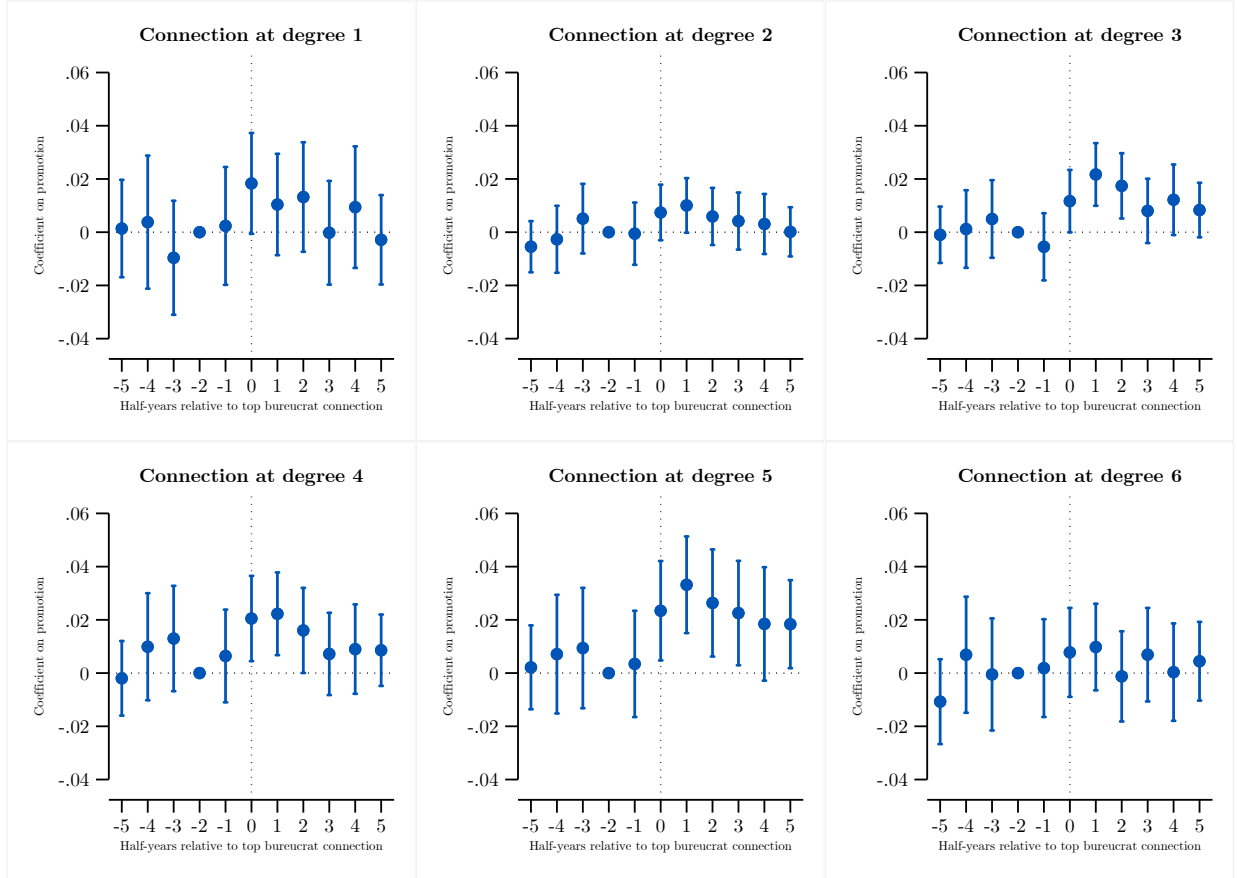


Notes: Figure displays the coefficients and 95% confidence intervals from the event-study of ever getting a family connection to a top bureaucrat (i.e., to a public sector manager or advisor) when looking at total earnings and hierarchical promotions as outcomes. It compares the coefficients estimated via the (Sun & Abraham, 2020) estimator and the OLS estimates. The OLS coefficients correspond to η parameters in the following econometric specification, where i indexes individuals, k agencies, f families, and t time periods.

$$E_{i,t} = \theta_i + \delta_t + \gamma_{k(i,t)} + \eta_5 \sum_{\ell \leq -5} B_{f,k,\ell}^{top} + \sum_{\ell = -4, \ell \neq 2}^4 \eta_\ell \cdot B_{f,k,\ell}^{top} + \eta_5 \sum_{\ell \geq 5} B_{f,k,\ell}^{top} + \mathbf{X}_{i,t}' \Phi + \xi_{i,t},$$

Standard errors are clustered at the dyadic family-agency level. The reference period is the year before the first family connection to a top bureaucrat (-2 half-years in the graph). Each set of coefficients in the figure is based on 6,390,117 panel observations coming from 722,366 bureaucrats and 34,887 connection events to top bureaucrats.

Figure A-9: Effects of Having a Family Connection to a Top Bureaucrat on Promotions by Degree of Separation

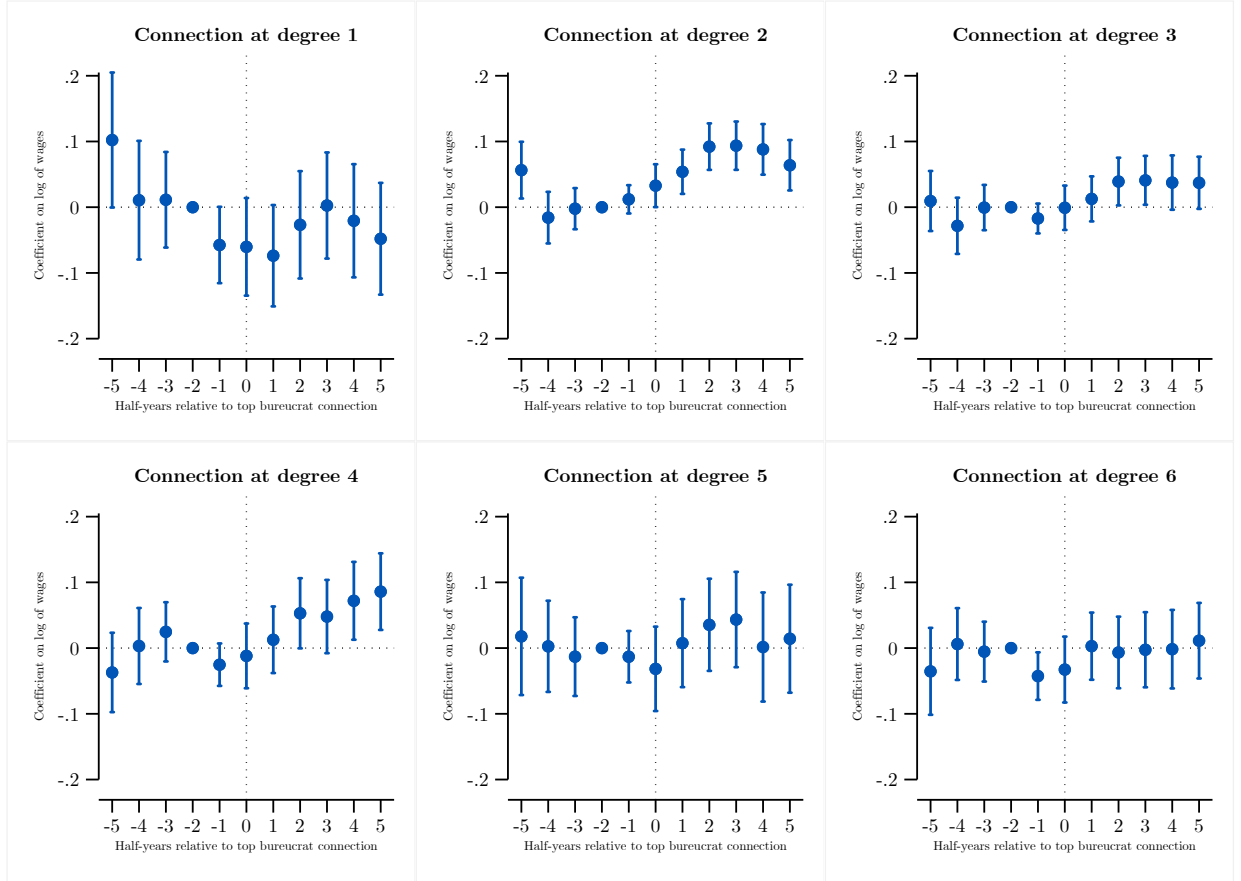


Notes: Figure displays the coefficients from the event study of getting a family connection to a top bureaucrat (i.e., to a top manager or advisor) when looking at hierarchical promotions as outcome. These coefficients correspond to η parameters in the following econometric specification

$$E_{i,t} = \theta_i + \delta_t + \gamma_{k(i,t)} + \eta_5 \sum_{\ell \leq -5} B_{f,k,\ell}^{top} + \sum_{\ell=-4, \ell \neq 2}^4 \eta_\ell \cdot B_{f,k,\ell}^{top} + \eta_5 \sum_{\ell \geq 5} B_{f,k,\ell}^{top} + \mathbf{X}_{i,t}' \boldsymbol{\Phi} + \xi_{i,t},$$

With 99% and 95% confidence intervals and standard errors clustered at the dyadic family-agency level. The reference period is the year before the first family connection to a top bureaucrat (-2 half-years in the graph).

Figure A-10: Effects of Having a Family Connection to a Top Bureaucrat on Earnings by Degree of Separation

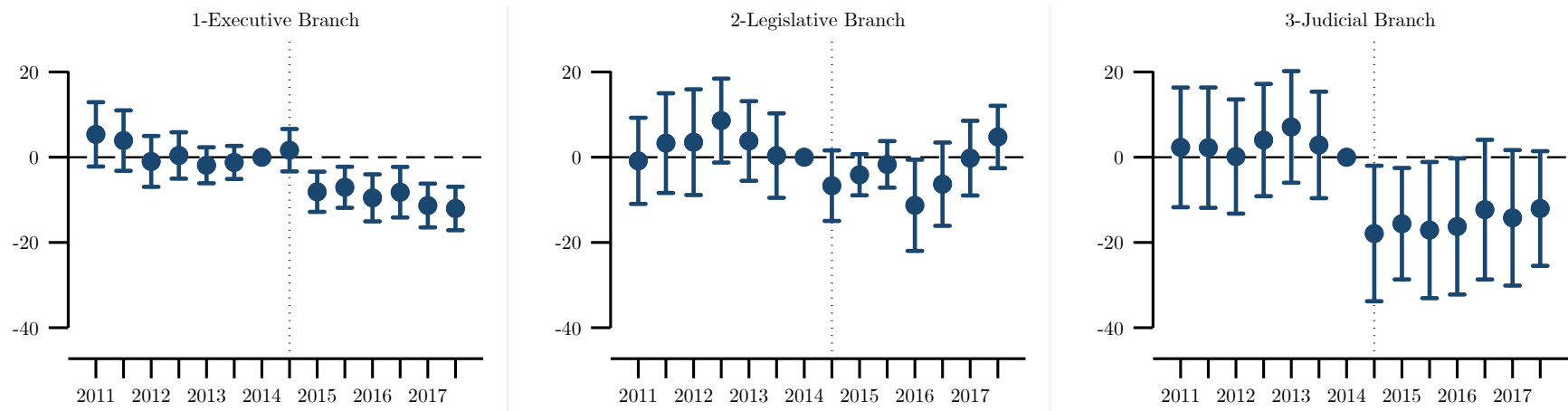


Notes: Figure displays the coefficients from the event study of getting a family connection to a top bureaucrat (i.e., to a top manager or advisor) when looking at hierarchical promotions as outcome. These coefficients correspond to η parameters in the following econometric specification

$$E_{i,t} = \theta_i + \delta_t + \gamma_{k(i,t)} + \eta_5 \sum_{\ell \leq -5} B_{f,k,\ell}^{top} + \sum_{\ell = -4, \ell \neq 2}^4 \eta_\ell \cdot B_{f,k,\ell}^{top} + \eta_5 \sum_{\ell \geq 5} B_{f,k,\ell}^{top} + \mathbf{X}'_{i,t} \boldsymbol{\Phi} + \xi_{i,t},$$

With 99% and 95% confidence intervals and standard errors clustered at the dyadic family-agency level. The reference period is the year before the first family connection to a top bureaucrat (-2 half-years in the graph).

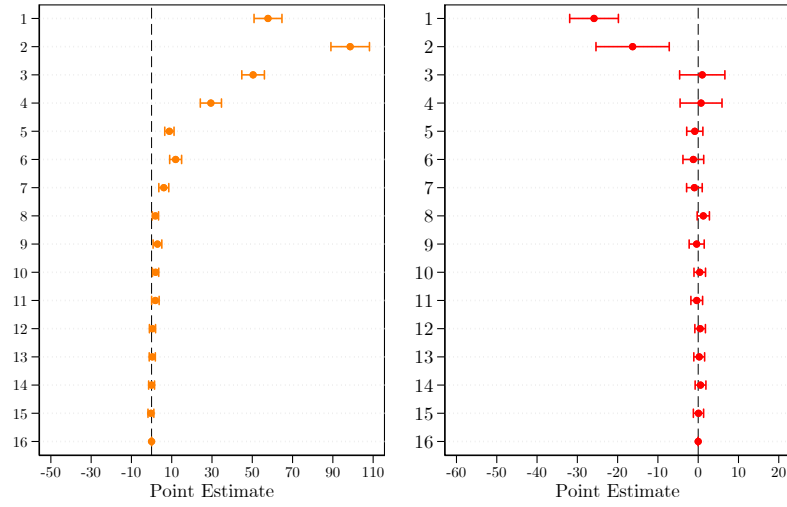
Figure A-11: Event Study Plot: Anti-nepotism legislation reform of 2015 differentiating branches of the government



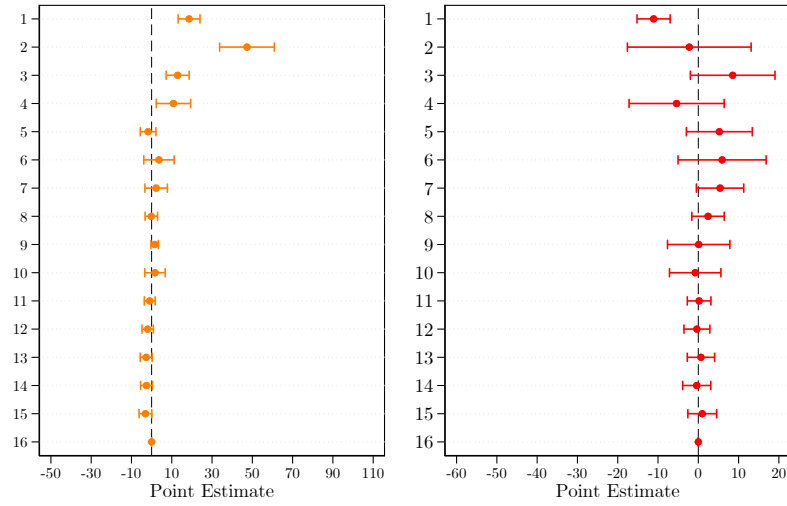
Note: Figure presents the point estimates and 90% confidence intervals corresponding to the coefficients β_{τ} in equation 9. The reference period is the first semester of 2014.

Figure A-12: Family connections and the introduction the anti-nepotism legislation of 2015: Differentiating the effects by degree of separation and branch of the government:

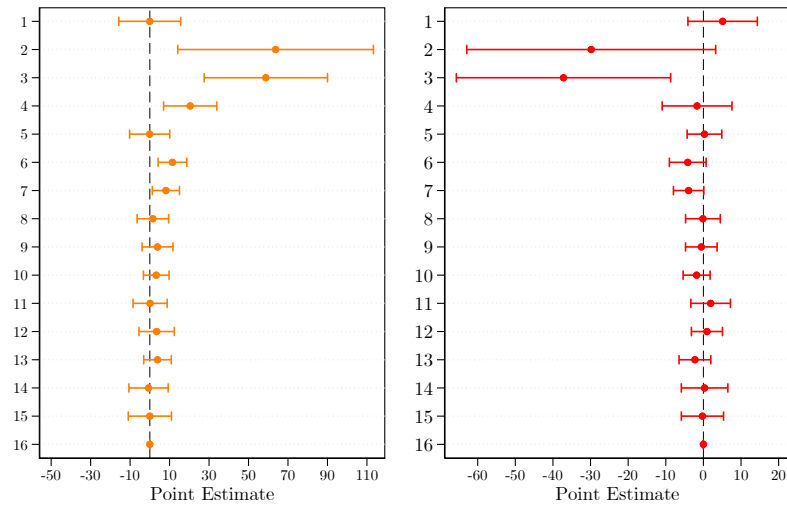
Panel A: Executive Branch



Panel B: Legislative Branch



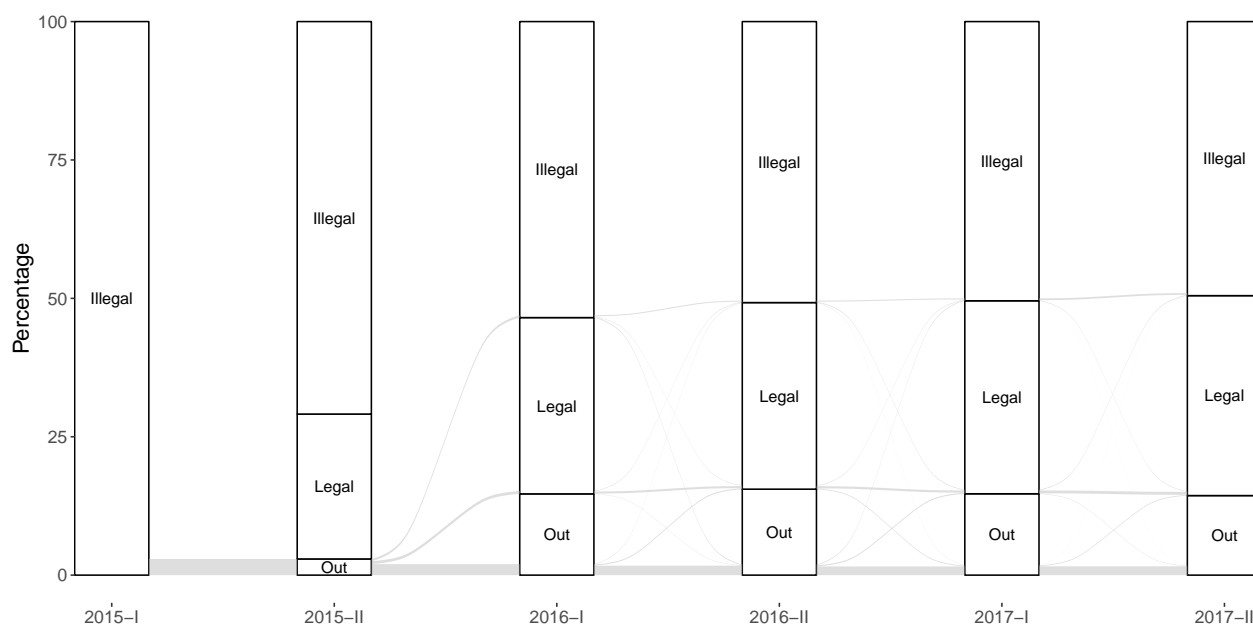
Panel C: Judicial Branch



Note: Figure presents the point estimates and 90% confidence intervals corresponding to the coefficients λ_ϕ and β_ϕ in Equation 10. The reference category are family connections at 16 or more degrees of separation.

Figure A-13: Initial compliance and subsequent recidivism

Panel A: Paths of those who leave the public administration in 2015-II



Notes: This figure shows the shares and flows over time of middle- and lower-tier bureaucrats who were part of an illegal connection in the first semester of 2015-I. Using this sample, the figure follows bureaucrats over time through three mutually exclusive states: “illegal,” “legal,” or “out”. The first state “illegal” is reached if bureaucrats stay put or become connected to another top bureaucrat at four degrees of consanguinity or less in the next period. In contrast, the “Legal” status is reached when bureaucrats move to another public sector agency where not family connection to a top bureaucrat exists at such degrees. Finally, bureaucrats get to the “Out” state when they leave the public administration by either moving to the private sector or unemployment. Hollow bars look at the fraction (i.e., the stock) of bureaucrats at each state labeled in the column. In gray, this figure presents flows of bureaucrats who “leave” the public administration in 2015-II.

Table A-1: Prevalence of anti-nepotism legislation by country income level

Income group	Anti-nepotism legislation	
	No (%)	Yes (%)
High income country	19.0	81.0
Upper middle income country	3.8	96.2
Lower middle income country	7.4	92.6
Low income country	0.0	100.0
Total	8.3	91.7

Notes: Cross tabulation based on 84 countries present in both the Worldwide Bureaucracy Indicators (WWBI) database and the World Bank worldwide governance indicators GovData360. Anti-nepotism legislation refers to the existence of regulations to prevent nepotism, cronyism, and patronage within the civil service according to the Global Integrity Index. Income groups defined by the World Bank. List of countries: AFG AGO ALB ARG AUT BEL BEN BFA BGD BGR BIH BOL BRA CAN CHL CHN CMR COL CRI CZE DEU DNK ECU EGY ESP ETH FRA GBR GEO GHA GTM HND HUN IDN IND IRL ITA JOR KAZ KEN KHM LBN LBR LKA LTU LVA MAR MDA MEX MNE MNG MOZ MWI NAM NGA NIC NPL PAK PAN PER PHL POL PRT PRY ROU RUS RWA SEN SLE SLV SRB THA TJK TLS TUR TZA UGA UKR URY USA VEN VNM ZAF ZWE.

Table A-2: Perception of favoritism by country income level, and anti-nepotism legislation

Income group	Anti-nepotism legislation		
	No	Yes	All
Favoritism by government officials is high (%)			
High income country	25.0	47.1	42.9
Upper middle income country	100.0	88.0	88.5
Lower middle income country	50.0	84.0	81.5
Low income country	-	50.0	50.0
Total	42.9	72.7	70.2

Notes: Cross tabulation based on 84 countries present in both the Worldwide Bureaucracy Indicators (WWBI) database and the World Bank worldwide governance indicators GovData360. Anti-nepotism legislation refers to the existence of regulations to prevent nepotism, cronyism, and patronage within the civil service according to the Global Integrity Index. Income groups defined by the World Bank. favoritism by government officials comes from The Global Competitiveness Report 2017-2018. The index goes from 1 = Never show favoritism to 7=Always show favoritism. I defined High favoritism as a dummy equal to one if the index is greater than 3.5. List of countries: AFG AGO ALB ARG AUT BEL BEN BFA BGD BGR BIH BOL BRA CAN CHL CHN CMR COL CRI CZE DEU DNK ECU EGY ESP ETH FRA GBR GEO GHA GTM HND HUN IDN IND IRL ITA JOR KAZ KEN KHM LBN LBR LKA LTU LVA MAR MDA MEX MNE MNG MOZ MWI NAM NGA NIC NPL PAK PAN PER PHL POL PRT PRY ROU RUS RWA SEN SLE SLV SRB THA TJK TLS TUR TZA UGA UKR URY USA VEN VNM ZAF ZWE.

Table A-3: Descriptive statistics at the individual level

Sample of individuals:	Non Top Bureaucrats		Top Bureaucrats		All Bureaucrats	
Observations:	$(n_{ntop} = 824,320)$		$(n_{top} = 175,792)$		$(n_b = 1,000,112)$	
Statistic:	Mean	SD	Mean	SD	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Woman	0.515	0.500	0.479	0.500	0.508	0.500
<i>Age at...</i>						
- date of entry into the labor force	29.375	9.224	29.340	8.594	29.369	9.117
- date of entry into the public sector	32.192	9.241	31.603	8.989	32.088	9.200
- the beginning of 2011	34.389	10.716	38.686	10.180	35.145	10.749
<i>Highest level of education is...</i>						
- Ph.D. degree	0.003	0.055	0.014	0.118	0.005	0.071
- masters degree	0.047	0.211	0.119	0.323	0.059	0.236
- specialization degree	0.130	0.336	0.352	0.477	0.169	0.375
- college degree	0.256	0.437	0.244	0.430	0.254	0.435
- less than college degree	0.564	0.496	0.272	0.445	0.513	0.500
<i>Has ever had a family connection to...</i>						
- any bureaucrat	0.407	0.491	0.481	0.500	0.420	0.494
- a top bureaucrat	0.232	0.422	0.298	0.458	0.244	0.429
- any bureaucrat in the same agency	0.143	0.350	0.180	0.384	0.149	0.356
- a top bureaucrat in the same agency	0.044	0.205	0.069	0.254	0.048	0.215
≡ Top Connected						

Notes: Observations at the bureaucrat level. Top bureaucrat refers to a bureaucrat in a hierarchical level of manager or advisor. Columns 1 and 2 present summary statistics for those individuals who never become top bureaucrats while Columns 3 and 4 correspond to the same statistics for those who become managers or advisors in the public sector at some point in their careers.

Table A-4: Descriptive statistics at the individual-time level by connectedness

Sample of individuals:	Non Top Connected		Top Connected		All	
Observations:	6,267,732		174,354		6,442,086	
Statistic:	Mean (1)	SD (2)	Mean (3)	SD (4)	Mean (5)	SD (6)
Wage (inverse hyperbolic sine of the wage)	9.223	0.975	9.234	0.958	9.224	0.975
Promoted	0.033	0.178	0.039	0.193	0.033	0.179
Public sector experience (half-years)	17.454	17.897	17.482	17.229	17.455	17.879
Private sector experience (half-years)	4.455	7.864	4.272	7.790	4.450	7.863
<i>Hierarchical position</i>						
- Professional	0.292	0.455	0.316	0.465	0.293	0.455
- Technician	0.092	0.289	0.107	0.309	0.092	0.289
- Clerical	0.189	0.391	0.155	0.362	0.188	0.391
- Contractor	0.427	0.495	0.422	0.494	0.427	0.495

Notes: Observations at the bureaucrat×half-year level. Top Connected refers to having a family connection to a top bureaucrat, i.e., a connection to a bureaucrat in a hierarchical level of manager or advisor.

Table A-5: Number of family connections within the same institution per ten thousand employees across different agencies

Number of family connections...	Below four degrees of consanguinity				Above four degrees of consanguinity			
	Mean (1)	Median (2)	Max (3)	IQR (4)	Mean (5)	Median (6)	Max (7)	IQR (8)
<i>Panel A: Branches of the government</i>								
- Executive Branch	223.0	158.1	5,001	195.9	136.4	65.8	5,000	185.2
- Legislative Branch	98.9	101.7	148.6	37.2	71.2	62.6	148.6	60.4
- Judicial Branch	151.9	92.4	546.5	90.4	140.1	84.3	632.3	117.1
- Autonomous And Independent								
- Control And Regulation	146.2	117.3	1,000	162.6	115.3	74.1	2,500	147.2
- Other	167.1	135.4	1,001	135.9	126.5	70.3	3,333	156.2
<i>Panel B: Level of centralization by functions</i>								
- Centralized functions	176.5	130.8	1,000	176.8	67.4	33.8	2,500	84.4
- Decentralized functions	178.0	111.6	5,001	141.2	41.0	0.0	3,333	37.7
- Mixed functions	261.1	200.0	5,000	204.9	58.8	0.0	2,000	61.7
Total	216.2	153.8	5,001	190.9	134.3	66.8	5,000	181.8

Notes: This table reports key summary statistics on the number of family connections per ten thousand employees within an agency across different groups of agencies. The unit of observation is institution-time. Sample includes all covered agencies from 2011 to 2017. IQR refers to the interquartile range

Table A-6: Agency performance and the presence of close family connections (government data)

Dependent Variable :	Agency Performance Index	Dimensions included in the performance index						
		Management of the Human Resources	Strategic Direction and Planning	Management by values towards Results	Evaluation of agency goals	Information and Commu- nications with Citizens	Management Knowledge and Innovation	Disciplinary Control
		(2)	(3)	(4)	(5)	(6)	(7)	(8)
Close family connections	-0.0728*** (0.0120)	-0.0442*** (0.0140)	-0.0736*** (0.0127)	-0.0613*** (0.0142)	-0.0712*** (0.0137)	-0.0715*** (0.0136)	-0.0730*** (0.0152)	-0.0786*** (0.0121)
Observations	3,853	3,853	3,853	3,853	3,853	3,853	3,853	3,853
R-squared	0.2183	0.1464	0.1881	0.2428	0.1755	0.2176	0.1523	0.2205

Notes: Observations are at the agency level. Sample includes all Public Sector agencies included in the *Medicion del desempeno Institucional* (MDI) database in 2016. Close family connections refers to the number of family connections below four degrees of consanguinity per one thousand employees within the agency. All columns control for the total number of employees. The table report the standardized (beta) coefficients, i.e., dependent and independent variables were standardized before estimating the regressions. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table A-7: Agency performance and the presence of close family connections (government data)

Dependent Variable :	Agency Performance Index	Dimensions included in the performance index						
		Management of the Human Resources	Strategic Direction and Planning	Management by values towards Results	Evaluation of agency goals	Information and Commu- nications with Citizens	Management Knowledge and Innovation	Disciplinary Control
		(2)	(3)	(4)	(5)	(6)	(7)	(8)
Close Family Connections	-0.0356*** (0.0124)	-0.0076 (0.0150)	-0.0247* (0.0128)	-0.0379*** (0.0145)	-0.0302** (0.0141)	-0.0352*** (0.0136)	-0.0252 (0.0155)	-0.0395*** (0.0123)
<i>Fixed effects</i>								
- Degree of centralization	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
- Administrative level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
- Branch of the government	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
- Type of agency (legal nature)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,853	3,853	3,853	3,853	3,853	3,853	3,853	3,853
R-squared	0.3747	0.2983	0.3484	0.3743	0.3313	0.3360	0.2730	0.3710

Notes: Observations are at the agency level. Sample includes all Public Sector agencies included in the *Medicion del desempeno Institucional* (MDI) database in 2016. Close family connections refers to the number of family connections below four degrees of consanguinity per one thousand employees within the agency. All columns control for the total number of employees. The table report the standardized (beta) coefficients, i.e., dependent and independent variables were standardized before estimating the regressions. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table A-8: Chaisemartin & D’Haultfoeuille (2020) Assessment of the problem of treatment heterogeneity in TWFE regressions

	Log(wage)	1(Promotion)
η^{TWFE}	-0.01676 (0.00249)	-0.00015 (0.00083)
Number of treatment effects	173,010	173,010
% of negative weights	18.14%	18.14%
$\underline{\sigma}_{fe}$	0.015764	0.000145

Notes: This table presents the estimates of the baseline regressions using TWFE based on non-staggered treatment adoption and OLS estimations. It also shows the total number of individual treatment effects based on which that estimate is computed and the percentage of treatment effects with a negative weight. The weights for each individual and time are then given by: $w_{i,t} = \frac{\epsilon_{i,t}}{\frac{1}{N_1} \sum_{(i,t): B_{i,t}^{top}=1} \epsilon_{i,t}}$ where $\epsilon_{i,t}$ is the residual of the regression: $B_{i,t}^{top} = \alpha + \theta_i + \delta_t + \epsilon_{i,t}$. Finally, $\underline{\sigma}_{fe} = \frac{|\eta^{TWFE}|}{\sigma(\mathbf{W})}$ is the minimal theoretical value of the standard deviation of the TEs across the treated individuals under which the average treatment on the treated (ATT) may actually have the opposite sign than η^{TWFE} . Notice that when $\underline{\sigma}_{fe}$ is close to 0, η^{TWFE} and the ATT can be of opposite signs even under a small and plausible amount of treatment effect heterogeneity. In that case, treatment effect heterogeneity would be a serious concern for the validity of η^{TWFE} .

Table A-9: Transition matrices

Starting period		Next period		
		2015-II		
		Illegal	Legal	Out
2015-I	Illegal	0.712739	0.258071	0.02919

Starting period		Next period		
		2016-I		
		Illegal	Legal	Out
2015-II	Illegal	0.433404	0.193795	0.08554
	Legal	0.096269	0.123816	0.037986
	Out	0.00464	0.004736	0.019814

Starting period		Next period		
		2016-II		
		Illegal	Legal	Out
2016-I	Illegal	0.410497	0.105741	0.018075
	Legal	0.095786	0.21042	0.016142
	Out	0.009472	0.016335	0.117533

Starting period		Next period		
		2017-I		
		Illegal	Legal	Out
2016-II	Illegal	0.391456	0.113377	0.010922
	Legal	0.098492	0.219505	0.014498
	Out	0.013339	0.020298	0.118113

Starting period		Next period		
		2017-II		
		Illegal	Legal	Out
2017-I	Illegal	0.398512	0.098299	0.006476
	Legal	0.09221	0.251885	0.009086
	Out	0.005993	0.013532	0.124009

Notes: This table shows the transition matrices across all pairs of periods of middle- and lower-tier bureaucrats who were initially part of an illegal connection in the first semester of 2015. The table follows bureaucrats over time through three mutually exclusive states: “illegal,” “legal,” or “out”. The first state “illegal” is reached if bureaucrats stay put or become connected to another top bureaucrat at four degrees of consanguinity or less in the next period. In contrast, the “Legal” status is reached when bureaucrats move to another public sector agency where no family connection to a top bureaucrat exists at such degrees. Finally, bureaucrats get to the “Out” state when they leave the public administration by either moving to the private sector or unemployment.