Getting Access to COVID-19 bailouts: Elite power or systemic importance?

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Getting access to COVID-19 bailouts: Elite power or systemic importance?

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Abstract

Using a novel database of 189,000+ Colombian firms and 500,000+ firm executives' names, I study the effect of financial factors, CEOs' centrality (corporate power), and political connections on access to a government bailouts program launched to subsidy wages in the first stages of COVID-19 crisis. Natural Language Processing algorithms and complex networks metrics are used to unveil ownership and control links of politic/economic elites and gauge their closeness to the Colombian President. I find that firm size factors and firm age, instead of political-connections or being run by prominent CEOs/shareholders, explain access to the program. In addition, I find that impacts of the program are positive in terms of salaries and liquidity, but they do not increase with firm size/age. These findings suggest a preference for protecting systemically-important firms (without ex-post economic efficiency) rather than special interests of elites.

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1 Introduction

The COVID-19 pandemic ushered an economic crisis around the world not ever seen since 1929. Latin American countries were severely affected by it.

This unexpected event prompted strong policy measures such as lockdowns, social distancing and banning of crowded events in the first months of the pandemic, affecting the financial situation of many enterprises in emerging countries. In June 2020, the Colombian annual GDP growth rate was -14.8%, and the unemployment rate reached 20.3% as the National Department of Statistics (DANE) reported. 266,091 enterprises went into bankruptcy since then. Fiscal and monetary tools were deployed to stabilize the downturn of the business cycle, and the government gave cash directly to enterprises and persons to prevent the economy from failure. The *Programa de Apoyo al Empleo Formal* (PAEF) is a salient example.

While such exceptional measures have received general support by the public, the extraordinary powers given to the President of Colombia by the Constitution during states of emergency and the high degree of secrecy around government-spending statistics have been controversial. Financial support to enterprises started only from the end of May 2020 (Observatorio Fiscal PUJ (2020)); informal enterprises were left behind on the basis that formal employment had to be prioritized (Observatorio Fiscal PUJ (2021b)). At the same time, large economic groups were benefited [1]. Similar controversies around selective bailouts sparked in the United States [2].

As recent research has that economic power structures are remarkably robust to shocks and that power remains extremely concentrated in the hands of a few individuals and organizations around the world (Glattfelder and Battiston (2019)), one would ask if such extraordinary powers given to the President were used by economic or political elites somehow to receive special support. This question is important because interest groups are a natural part of Western democracies (Bar-Yam (2018)), and it is reasonable to think that in turbulent times interests of some firms would be

[1] La W Radio (2020). "Los grandes grupos económicos que recibieron ayudas durante la pandemia".

[2] The Washington Post (2020). "Doomed to fail: Why a $4 trillion bailout couldn't revive the American economy". As Autor et al. (2022a) have mentioned about a program to help U.S. businesses, "The majority of loan dollars issued in 2020—66 to 77 percent— did not go to paychecks, however, but instead accrued to business owners and shareholders. And because business ownership and share-holding are concentrated among high-income households, the incidence of the program across the household income distribution was highly regressive".

protected over the others to maintain their status quo (Johnson and Mitton (2003), Jackowicz et al. (2020)). However, it could also be possible that those firms, because of their size or age (and thus because of their importance in terms of employment), received special support because of their systemic-importance to the economy in terms of employment, so instead of protecting the interests of the wealthiest, the program was aimed to protect employment as much as possible to secure a fast recovery. Both competing possibilities have to be explored empirically. Finally, as an ex-post evaluation, one would ask if, in case that any of those factors were found significant in access, they can be considered as sources of heterogeneous effects, so one can evaluate if the focus of the program was ex-post correct or not.

In this document, I analyze if the prominence/political power of CEOs/shareholders or firm-size factors were important in getting bailouts during 2020 under *Programa de Apoyo al Empleo Formal* (PAEF), the impact of the program in terms of salaries and liquidity and its heterogeneous effects. For this purpose, I exploit information of executives of 189,000+ firms and a panel of annual financial information for 11,000+ firms from 2017 to 2020. Natural Language Processing and Complex Networks algorithms are used to measure the political-power/prominence of executives. The link between network centrality and access to bailouts is explored with regressions with fixed effects, and identification of ex-post effects of the policy is obtained with difference-in-differences (DiD).

There are two contributions to the literature. To the author's knowledge, this is the first empirical study in which the political and economic influence of firms on public policies are analyzed separately, a different approach compared to previous works on political connections literature (Acemoglu et al. (2016), Johnson and Mitton (2003), Faccio et al. (2006)); and is one of the first ones in analyzing the impact of government policies for firms during COVID-19 in emerging economies. For this purpose, I make a large-scale reconstruction of the structure of ownership and political power in Colombia following the approach of Glattfelder and Battiston (2009) to understand power as a complex-systems phenomenon, and I use microdata of benefited/non-benefited firms under PAEF.

Regression results suggest a preference for protecting systemically-important firms in terms of employment without ex-post efficiency rather than defending special interests of elites: firm-size factors (total revenues and firm age) but not prominence/political power of executives were important in receiving PAEF subsidies after controlling for financial, geographical and informational covariates. However, neither firms' size nor firms' age were significant to explain heterogeneous effects of the program. The overall effect of the program is strongly positive, with differential effects by industry. The ATT estimated effect is equal to 24.3% in expenses in salaries and 32.9% in firms' liquidity measured as cash ratio (the ratio between cash/short-term securities and the current liabilities).

These results must be interpreted cautiously. Newer information is needed to evaluate long-term effects; estimating precise values is difficult as there is no public information on total disbursed amounts for each firm; and evidence regarding to political-power/prominence must be considered suggestive on the ground of the opaque nature of Politics in a non-experimental environment.

The order of the document is as follows. Section II provides a context of the program; in III, a description of the different datasets used is presented. In IV, I present the methodology used for calculating measures of network prominence and political closeness to the President of Colombia and the empirical framework. In V, I present a descriptive analysis of the data collected. In VI, I show the analysis results, and in VII, the document presents the main conclusions.

2 Context

In the spread of the COVID-19 pandemic in March 2020, governments worldwide launched subsidies and bailouts programs at an unprecedented scale to mitigate systemic economic risks not seen in one century. A timeline of the creation and modifications of the PAEF program, a program launched in Colombia, is presented in Figure 1.

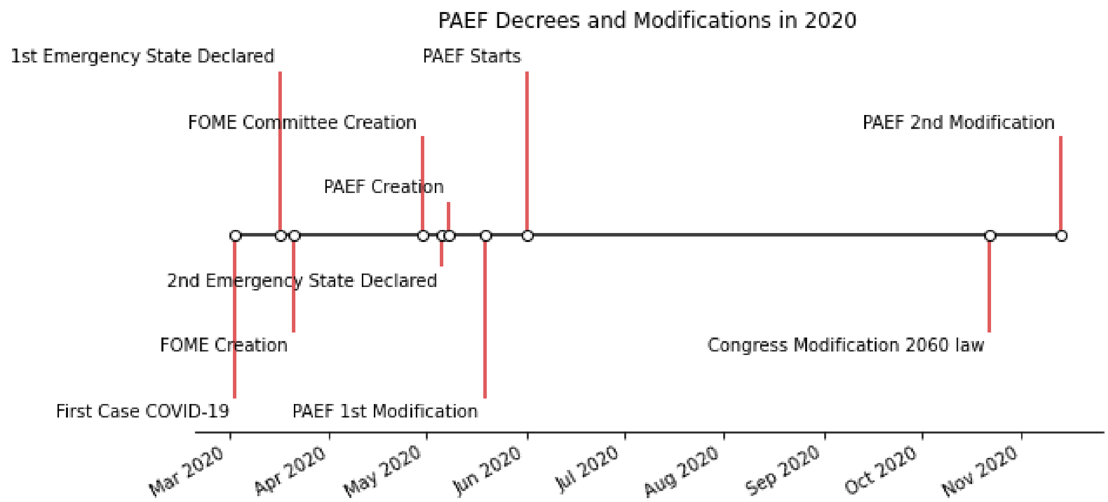


Figure 1: ***Timeline of PAEF decrees and modifications through 2020.***

As in many Latin American countries, the Colombian government responded by announcing the first state of emergency [3], for which the President of Colombia ordered the creation of a government fund (FOME, *Fondo de Mitigación de Emergencias*) [4] to inject money into the economy through economic policies and mitigate the crisis, given that nearly five million jobs were suddenly lost. More particularly, a bailouts program for financially-troubled companies – *Programa de Apoyo al Empleo Formal*, PAEF - was launched two months later with resources from this fund [5], consisting of subsidizing the wages of its employees partially. The Ministry of Finance was in charge of its design and possible modifications. One of its main units – *Unidad de Gestión Pensional y Parafiscales*, UGPP - was ordered to lead the verification of documents provided in applications and determine if companies were eligible for the cash-aid. After several modifications ordered by the budget committee [6], the program started at the end of May by covering April payrolls. In October, the Colombian Congress approved additional amounts for certain industries and per woman employee, deciding

[3] Presidencia de Colombia (2020a). The first case officially registered in Colombia was on March 6th.

[4] Presidencia de Colombia (2020b). The fund was formed with loans and cash in consonance with the 444 Decree. Loans came from FAE (*Fondo de Ahorro y Estabilización*), FRL (*Fondo de Riesgos Laborales*) and FONPET (*Fondo Nacional de Pensiones de las Entidades Territoriales*), and cash from temporary personal taxes (*Impuesto solidario*) among other sources. A FOME Committee was created under 1065 Resolution (Ministerio de Hacienda (2020a)), one month later. Its purpose was the technical coordination and monitoring support of FOME resources.

[5] The second state of emergency was declared in the first days of May under 637 Decree (Presidencia de Colombia (2020c)) and PAEF program was created two days after day under 639 Decree (Ministerio de Hacienda (2020b)).

[6] The original design did not include natural persons as beneficiaries, so a new version was created under 677 Decree (Ministerio de Hacienda (2020c)). Coverage of partnerships was added in 815 Decree (Ministerio de Hacienda (2020g)).

also to extend the program until March 2021. This modification took place in November [7]. With large design-changes, the program was reactivated in September 2021 [8].

A set of requirements to apply was established:

- The benefit was proportional to the number of employees earning more than one minimum legal wage and with legal benefits paid up to date. 80% of these employees must have appeared in the February 2020's list of employees according to PILA (*Planilla Integrada de Liquidación de Aportes*) database, a national registry of health and pension contributions. There were no aids for the informal sector, businesses that went bankrupt until May, or natural-person companies with less than three employees.
- The company must register revenue reductions larger than 20% between January 2020 and March 2020 or the 2020-2019/2021-2020 annual change in a particular month. Joint verification processes with others institutions (such as DIAN and Confecámaras, as is explained later) registers secured the veracity of data provided.
- Companies must register saving or checking accounts in a financial institution.
- Companies must have a 2019 commercial register/license.
- Public-sector entities must own less than 50% of equity in benefited companies.

As benefits, under the 677 Decree the bailouts program gave a subsidy of $350.000 COP (40% of minimum legal wage) per employee and month, regardless of the size of the enterprise, industry, or percentage of losses greater than the threshold. Under the 2162 Resolution issued in November 2020, the subsidy increased to $439.000 COP per women employee or if the company was associated with a highly-damaged industry (sports, art, culture, recreation, or tourism). From this last Resolution, the threshold of minimum percentage of employees required to receive benefits of 80% was reduced to 50%.

[7] Ministry of Finance issued in November a decree announcing modifications after Congress passed 2160 law (Congreso de Colombia (2020), Ministerio de Hacienda (2020f)). Retroactive payments were made from September under this petition.

[8] Under 2155 Law of 2021, the program targeted mainly small-businesses, but the focus of analysis here is only 2020.

3 Data

There exist seven data sources used in this paper. Five are used to estimate main regressions and two to check robustness.

The first source is a dataset of 189,542 firms, integrating information over four years (from 2017 to 2020) from Confecámaras (*Confederación Colombiana de Cámaras de Comercio*), a non-profit private entity amalgamating 57 chambers of commerce -; Supersociedades (*Superintendencia de Sociedades*), a regulatory institution that exercises the inspection, surveillance and control of commercial companies; and Superfinanciera (*Superintendencia Financiera de Colombia*), a regulatory institution of the Colombian financial system. The dataset covered information of 523,657 Board of Directors and shareholders' complete names and their job titles in December 2019, name of the company, CIIU/NIT codes, municipality of headquarters, main address, and balance sheets variables [9]. Only annual information was exploited as quarterly information was limited to 959 listed companies (local derivatives, corporate bonds, and stock markets are very small and illiquid). There are 466,979 links between CEOs' names and firms. A Natural Language Processing methodology to account for name similarity is explained in the next section, as ID numbers of Boards of Directors and shareholders were unavailable.

The second is a list of 118,433 NIT codes representing non-natural companies that benefited from PAEF from May 2020 to January 2021. It was released in March 2021 on the Ministry of Finance-UGPP website [10]. 54% of benefited firms (63,594) are registered in the *Confecámaras* database by comparing NIT codes.

Regarding to politically-connected-to-President firms, there are three datasets of interest [11].

The first one is a list of donors to members of Congress (all active before June 2020) and Presidential candidates during the 2018 elections (two years before the pandemic) extracted with web-scrapping from the National Electoral Council's databases (*Cuentas Claras*), covering information

[9] Data about property-equipment (P&E) was scarce, so I added information for some companies from SIIS (*Sistema Integrado de Información Societaria*).

[10] Unfortunately, the list of beneficiaries per month is not publicly available. Up to March 2021, 142,299 were benefited, but the focus here is 2020; hence I use the first database published.

[11] The same type of datasets has been used in the political-connections literature (e.g. Faccio et al. (2006); Ferguson and Voth (2008); Johnson and Mitton (2003)).

of 2,196 donors with complete names to 261 political figures' campaigns. This information is self-reported. Creditors' names (persons and enterprises) were pulled out to extract 6,757 significant links at the end.

The other one is a database built manually from websites of a 2018 report published by *Cuestión Pública*, an independent journalistic-research organization, with comprehensive information of 3,405 links between entrepreneurs, elected Congress members (86 of 106 Senate members and 5 of 155 House of Representative's members) and their families [12]. The quality of this dataset is guaranteed as they present information about coalition and opposition parties' members; its fundraising depends on donations of citizens; and the evidence is revealed through photos of property titles, judiciary processes, social media posts, and RUES (*Registro Único Empresarial y Social*) or DIAN (*Dirección de Impuestos y Aduanas Nacionales*) registers.

The last source of political-connected firms is a dataset retrieved with web-crawling from *La Silla Vacía* (*Quién es Quién* section), another independent media-communications company focused on analyzing and reporting political news of the country [13]. It contains information on 1,878 links of political alliances and personal relationships among 495 recognized figures of the country (with complete names) from 2017. Rivalry and professional relationships are excluded to ensure that only strong connections are drawn.

Acknowledging that informational factors might have driven application to the PAEF program, I collected 5,290 addresses of all commercial branches of 30 banks and credit unions registered as PAEF intermediaries in 0801 Resolution (Ministerio de Hacienda (2021)). Through geocoding, I calculate Vincenty's averaged distances between firms and the nearest bank branch to test the influence of this factor as robustness [14].

Finally, as human capital factors (business knowledge/unobserved professional abilities) might confound CEOs' centrality, I use information of nationality, gender, age, if she/he has been a public servant, and education level of the 846 most important Colombian CEOs during 2017, 2018 and

[12] Specifically, information from three websites associated to *Cuestión Pública* was gathered: "We know what you did in past legislature", "We know what you did", and "We know what you did – reloaded".

[13] "La Silla Vacía - Who is Who". Eighty pages were web-crawled.

[14] As stated by personal interviews, the whole application process was done in the internet mostly, but applicants could also go to bank branches. It was mandatory to have an active deposit account (57.3% of corporate entities met this requirement) and going to bank branches in case of inconveniences.

2021, published by *La Silla Vacía* (*La Silla Datos* section). Complete information was found for 617 of them.

4 Methodology

In the following lines, I describe the technical process of calculating measures of network prominence and political closeness to the President of Colombia as treatment variables. The list of CEO and shareholder names in raw data contains unique names written differently; hence my first objective is to drop duplicated names. With this cleaned dataset, I built a network of persons and enterprises connected through ownership and control links to determine a ranking of the prominence of persons in the network. Then, with a set of assumptions, I use political connections datasets and information of the network to calculate the distance between CEOs/shareholders and the President of Colombia. Next, calculating these continuous treatment variables, I describe the definition of treatment and control groups. Finally, I illustrate the estimation framework of access and economic efficiency of bailouts.

4.1 Identification of Ownership/Control links

In this subsection, I will explain the methodology used to drop duplicated names from raw data to obtain a clear representation of owner and control links between persons and enterprises. I begin determining names of influent people within each firm by selecting specific job titles, filtering out fiscal/tax auditors, operative managers, and personnel arguably not heavily involved in management decisions [15]. Because of a scandal in which fictitious names were registered as CEOs in environmental organizations during October 2019 board of directors elections in a public entity, I dropped some other names [16].

Since ID numbers are not available to identify which firms are controlled by particular CEO or shareholder, the same problem faced by Ferguson and Voth (2008), a Natural Language Processing

[15]The list of job titles selected is presented in Appendix A. I also dropped defuncted persons up to December 2019.

[16]El Tiempo (2019).“Líos detrás de las elecciones en la CAR Cundinamarca”. Fictitious names mentioned in this article are ”Flor Alba Roa de Herrera”, ”Maria Fernanda Reyes Barahona”, ”David Stivel Reyes Barahona”, ”Fernando Herrera Saldaña” and ”Yherson Daniel Herrera Fuentes”. I also dropped the name of a tax auditor involved in judicial scrutiny according to the Central Board of Accountants (JCC) webpage.

(NLP) approach to retrieve as much information as possible from the *Confecámaras* dataset is made. Specifically, I exploit the structure of person names in Colombia to identify duplicated entities and obtain a reliable representation of network prominence. The methodology is as follows:

According to the National Registry of Colombia, each person's name have a definite sequence specified in the following example:

Name: [Martín] [José] [Ferrer] [de la Hoz]

Structure: [First Name] [Second Name] [Father Last Name] [Mother Last Name]

As long as names in the original database are written in disorder, I rewrote each CEO name of the database in the form of this sequence using Named-Entity Recognition algorithms, as is illustrated in Figure 2 [17].

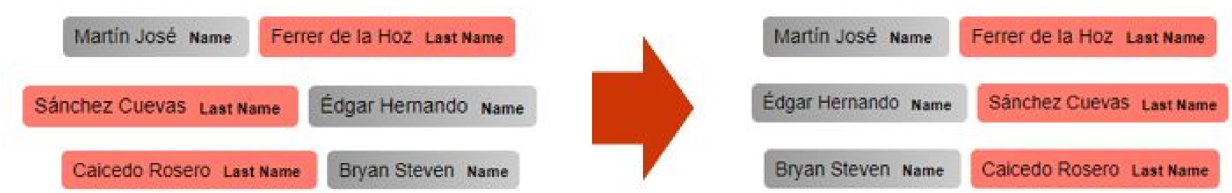


Figure 2: ***Names reordering with Named-Entity Recognition.***

This reordering is vital because it makes it easier to tackle the next step, consisting of finding all possible duplicated names. Addressing this possibility is necessary to understand correctly the ability of control of each CEO or shareholder across different industries.

Methodologically, a Ratcliff-Obershelp similarity matrix of size 713,199 x 713,199 was calculated to compute scores of all possible duplicated CEOs' names through pairs of matches [18]. A drawback of this algorithm is the high number of matches with scores equal to 0.9 and 0.95, so

[17] Since enterprises and persons can be shareholders, I predict if each sequence is associated to a CEO/shareholder or firm and next I predict the last name to each sequence predicted as CEO. Technical details of these deep learning algorithms are presented in Lample et al. (2016). The library *Spacy* available in Python was used. A random sample of 1,200 out of 598 CEO names and 2,196 firm names was trained together with their category ("PERSON" or "ENTERPRISE") to predict the category of all sequences. Another random sample of 1,200 out of 3,189 CEOs' names was trained together with their respective last names to predict the names and last names of all CEOs and shareholders.

[18] Technical details of the Ratcliff and Metzener (1988) algorithm to calculate the phonetic similarity of names are presented in Appendix **??**. I used parallel computing to accelerate the calculation of this matrix with *numba* library in Python.

a deep learning algorithm was trained to predict more high-quality scores for these values and define more accurate matches [19].

With a definite list of possible matches between CEOs/shareholders' names and a score of the quality of these matches, a final part of the methodology is the manual review of results produced by the algorithms [20]. Expert criteria to decide whether certain pair of CEOs' names constitutes a suitable match becomes necessary at this point. Following the above example of ”Martín José Ferrer de la Hoz”, let us suppose there are five possible matches for this name:

(I) Martín José Ferrer de la Hoz, Martín José Frrer de la Hz .

(II) Martín José Ferrer de la Hoz, Martín Ferrer de la Hoz.

(III) Martín José Ferrer de la Hoz, José Ferrer de la Hoz.

(IV) Martín José Ferrer de la Hoz, Martín José Ferrer.

(V) Martín José Ferrer de la Hoz, José Martín Ferrer de la Hoz.

In order to preserve the ordered global structure of registered names, a good match is defined to be found for cases (I) and (II). In Case (I), the letter ”e” is omitted in ”Frrer” and ”o” in ”Hz”, but the structure of the name is almost the same. In contrast, in Case (II), the second name is omitted, but it is defined as a good match, considering that in Colombia it is a widespread practice to report only the first name followed by last names. Case (III) is excluded because, as a complement to Case (II) is not common practice to report only second names. Case (IV) is excluded on the ground last names must be revealing enough to consider whether there is a good match or not. Case (V) is ruled out because the original order of first names is preserved, so ”Martín Jose” and ”José Martín” are considered different CEOs.

Of course, this approach has limitations. There exists the risk ”Martín José Ferrer de la Hoz” and ”Martín Ferrer de la Hoz” refer to different CEOs, or even ”Martín José Ferrer de la Hoz” is

[19] Specifically, I trained a Long-Short Term Memory Model (LSTM), developed by Hochreiter and Schmidhuber (1997). The accuracy obtained was 0.79.

[20] Manual review gives the final decision, but the Named-Entity Recognition algorithms trained earlier were used again to create dummies for Cases (I)-(V) mentioned here below.

a shared name for two or more CEOs. Matching names shared by different persons can be problematic. However, arguably three facts help to deal with this issue: the database is clean enough to include only influential persons within each firm, information of four names reduces the possibility of bad matches, and is anecdotally known people with ages greater than 51.5 years (the average value of CEOs/shareholders in the sample, so the bulk of CEOs and shareholders is not composed by young people) exhibit uncommon names.

This methodology, intended to drop duplicated names as much as possible and also used to concatenate names of different databases through names, let me establish with clarity which firms a CEO/shareholder exercises control/ownership. This property of the cleaned dataset is exploited to measure the network prominence of each CEO/shareholder in the next section.

4.2 Measuring network prominence of CEOs and shareholders

To gauge the network prominence of each CEO and stakeholder, a complex-network approach is followed in this section. Networks are used in social and natural sciences to understand a large number of parts that interact in a non-simple manner, such as banks in the financial system, animals in a forest, users in a social network, or shareholders in ownership networks (Simon (1962), Glattfelder and Battiston (2009)).

Given that networks are a natural representation of complex systems, shareholders and CEOs are elements of a large system, in which they exercise power on individual companies and, more indirectly via ownership, on other companies through her/his decisions (Glattfelder and Battiston (2019)). By representing ownership and control links as a network, CEOs and shareholders (in the form of persons or enterprises) are depicted as interconnected nodes when they exercise power on Colombian companies by December 2019 (three months before the pandemic). Such exercise of power is represented graphically through arrows representing links.

With the database of enterprises and CEOs, free of duplicated names as much as possible, I represent all ownership and control relations with a matrix containing all links from CEO/stakeholders to each firm, named *adjacency matrix* (A), that represents a directed-unweighted graph. Let n represent the sum of all CEOs, shareholders and enterprises of the database, A is a matrix of dimensions n x n, with each element $a_{[c,s],f}$ being zero or one depending if certain CEO c or shareholder

s exercises ownership or control respectively on firm f or not [21]:

$$A = \begin{bmatrix} 0 & a_{12} & a_{13} & \dots & a_{1n} \\ a_{21} & 0 & a_{23} & \dots & a_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & a_{n3} & \dots & 0 \end{bmatrix}$$

In this matrix, ownership and control links are treated as the same type on the basis I try to obtain the most straightforward representation of ownership and control. This is a different approximation compared to previous works of corporate power in director bipartite-graphs (Battiston and Catanzaro (2004)) and ownership weighted-networks (Glattfelder and Battiston (2019)), as the main objective is to analyze all potential roads of influence during turbulent times, CEOs and shareholder roles are not comparable by definition, and there are too few data about the degree of ownership of each shareholder in each enterprise.

Graphically, different links between CEOs, shareholders and enterprises emerge with the information summarized in this matrix, drawing some examples in Figure 3.

To interpret this figure, let us suppose three persons, A (shareholder), D (CEO), E (CEO) and two firms (Firm 1, Firm 2), all represented with circles (*nodes* in the complex networks literature). Each arrow, named *edge* in the literature, represents an ownership relationship (all arrows flowing from shareholder A to firms) or control relationship (all arrows from CEOS D and E pointing to firms). Therefore, each of the three graphs in this figure represents a possible case: in the upper left graph, shareholder D exercises an ownership relation over Firm 1 and this firm on Firm 2, so D exercises indirect ownership on Firm 2. In the lower left graph, Firm 3 exercises ownership of a firm with the same name of person A (in Colombia, company names can be the same as the names of a main executive), shareholder of Firm 2. In the right graph, CEO D exercises control over Firm 1, CEO E over Firm 2, and shareholder A exercises ownership power over Firm 2.

[21] This means the power of each person is assumed to be equal within each firm, so there might be an underestimation of effects.

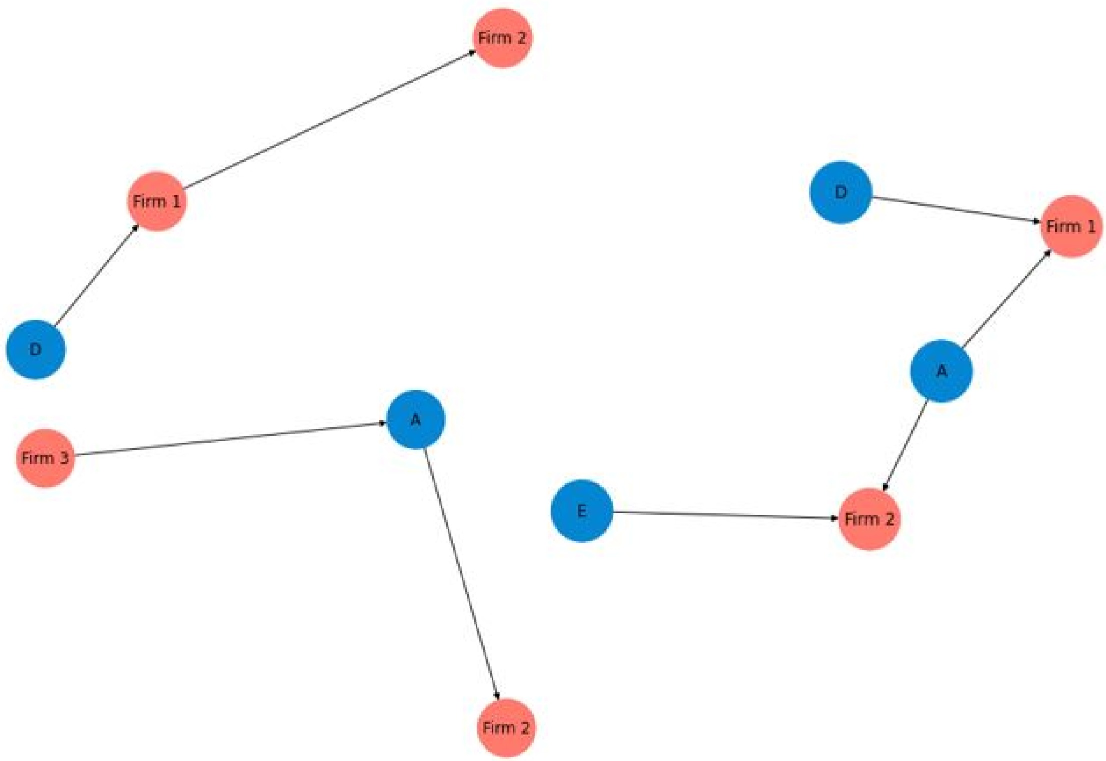


Figure 3: ***Graph representations of ownership and control links between CEO, shareholders and firms.***

To the extent some CEOs or shareholders are registered to exercise power on many firms or few firms that in turn legally exercise control on many others, a hierarchical structure of ownership arises from these graph representations: some CEOs or shareholders have more influence than others because they exercise power on 60 firms or in 10 firms that control too many others at the same time most of them on only one, and by this way, their decisions are much more critical in terms of firms' performance and degree of influence in economic policies. In the context of the COVID-19 economic crisis, such asymmetry can be outstanding, as regulatory capture or influence buying becomes necessary to push government intervention in helping financially-troubled firms, especially in developing countries (Johnson and Mitton (2003)).

The graph representation of the total ownership and control network built is relatively equal to the shown in Figure 4, taken for illustration purposes from Glattfelder and Battiston (2019), where each color of nodes represent some industry.

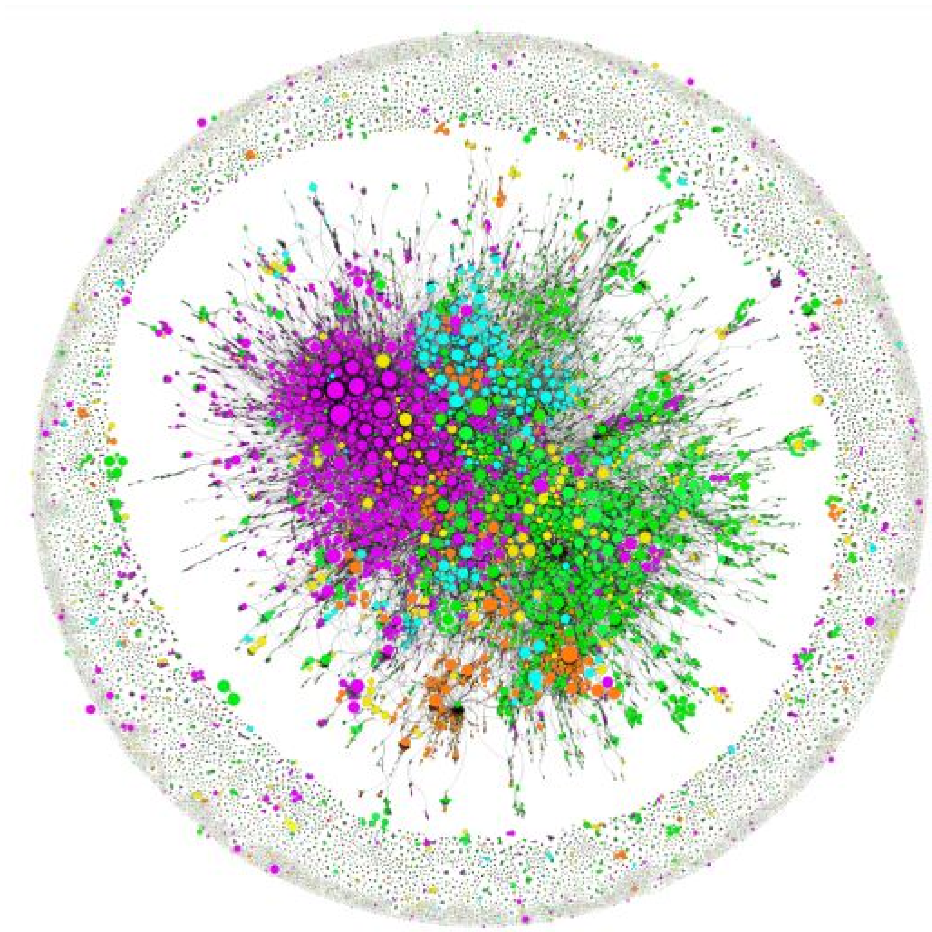


Figure 4: ***Ownership and control network of enterprises.***

From the figure can be seen a large subset of nodes (CEOs, shareholders, firms) being part of a single group (center of the graph); at the same time, there are plenty of individual and disconnected nodes, forming in some cases tiny groups. The size of nodes is proportional to assets volume. As the first group amalgamates the country's largest firms in terms of assets, CEOs and shareholders of this group arguably have high network prominence, much more than shareholders or CEOs of firms located outside. Any measure must address this observation in the search for quantifying network prominence.

Network ranking measures come to the rescue in this search. By assigning a numerical weighting to each node within the graph according to their prominence, mathematical features of the matrix A defined above are used to establish the structural ability of each node to influence others. In this paper, the network prominence of each CEO and stakeholder is measured with a PageRank score, a ranking measure calculated by an algorithm developed by Brin and Page (1998). This algorithm, initially aimed to rank Google searches by its proponents, is widely used in ranking scientific journals, webpages and influential users on Twitter [22]. PageRank scores are based on the idea that the prominence of a CEO/shareholder is determined by: (i) the number of firms in which she/he exercises control; (ii) the prominence of controlled firms that, in turn, exercise control over others, directly or indirectly. Direct or indirect ownership/control of highly ranked enterprises contributes more than lower-ranked enterprises, so this measure establishes a hierarchy of executives. For robustness checks, I will present results with degree, eigenvector and closeness as alternative centrality measures, used by Cruz et al. (2017) and explained in Appendix E.

The maximum value of PageRank score across all shareholders and CEOs within each firm is the treatment variable I use to determine the impact of being network-prominent on access to the PAEF program [23]. To the extent prominence or centrality measures are based on networks and express intangible and individual characters, they can be considered highly informative, as has been shown statistically in recent literature (Cruz et al. (2017), Naidu et al. (2021)).

4.3 Measuring political closeness to the President

In this section, I explain the methodology to calculate the closeness between the President of Colombia and politically-connected firms, the treatment variable created to measure the impact of political connections on access to the bailouts program.

As measuring political power is quite tricky, and even network data available cannot give us an exact map of actual political links because of its secretive nature, it is reasonable to make assumptions and use the most available technologies to uncover hidden links as if detective research, in the same way of Padgett and Ansell (1993). I will use the political-connections datasets to calculate the political closeness between politically-connected CEOs or shareholders and the President.

An implicit but general assumption is made: political friendships and donor links before the COVID-19 pandemic mirrored the structure of political connections with the President in the first

[22]Technical details are presented in Appendix E. Traditional network ranking and centrality measures have been criticized by Glattfelder and Battiston (2019) because these ownership networks display bow-tie structures in which these measures are not very accurate. As my objective is not an *exact* ranking per se, this criticism is mitigated in some way.

[23]Median/averaged values for each firm do not change general results, as it is shown in the results section.

semester of 2020 [24]. More concretely, a set of three assumptions supported by relevant literature is followed:

Assumption 1 (Political alliances within coalition parties)**.** *During the beginning of the COVID-19 crisis, Congress members of coalition parties but not opposition parties built cooperative alliances within and with the President to attend demands of economic elites.*

In accordance with Box-Steffensmeier et al. (2020), collaboration between members of Congress is most likely between those from the same party or geographical region. This makes sense during periods of high economic uncertainty, where extraordinary decision must be taken quickly. Cooperative alliances with the President, on the other side, are assumed strong because the official party (*Centro Democrático*) has maintained unity in approving tax reforms and social investment projects as Congress bills from 2018.

To represent a political network with these elements in mind, I define bidirectional links among all congressmen *within* each political party that ratified support of the second state of emergency by which the PAEF program was created [25], and assigned bidirectional links to each of them with the President. The list of parties involved is as follows:

- *Partido Colombia Justas Libres*.
- *Partido Centro Democrático*.
- *Partido Social de Unidad Nacional*.
- *Movimiento Independiente de Renovación Absoluta* (*MIRA*).
- *Cambio Radical*.
- *Partido Conservador Colombiano*.
- *Partido Liberal Colombiano* [26].

[24] A caveat of this assumption is regarding to donors information: donors links might be driven by economic-connections, so political connections are not reflected purely.

[25] Senate of the Republic of Colombia (2020). "Senado respalda decretos de emergencia económica expedidos por el Gobierno para enfrentar COVID-19". While most coalition parties supported the decision in August 2020, opposition parties rejected it.

[26] Although Liberal Party is not part of the coalition, its support of the state of emergency is taken as proof of temporal closeness with the President.

Relationships represented are drawn in Figure 5. Congressmen C2, C3 and C5 of the same coalition party create links with themselves and with the President, happening the same to congressmen C1 and C4 of another party.

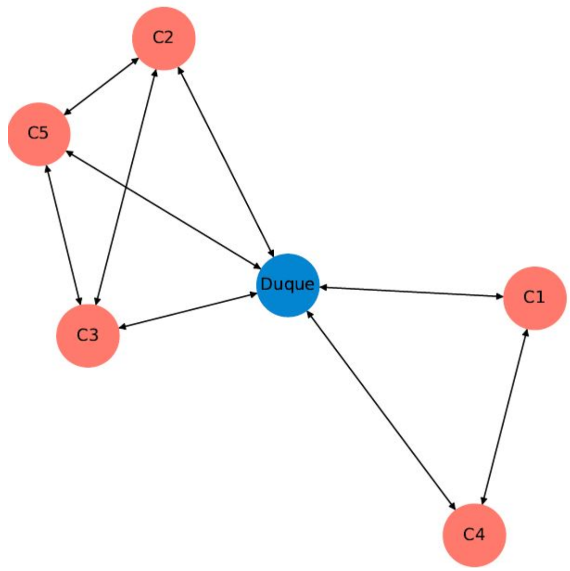


Figure 5: ***Graph representation of President - Congressmen relationships.***

Assumption 2.a (Donors links)**.** *Donations to political figures' campaigns in 2018 signaled political connections at 2020.*

Although there is no literature about the link between donors and Congress Bills in Colombia to the author's knowledge, Ruiz (2021) documents that donations to municipality majors constitute a significant channel to win discretionary procurement contracts when the preferred candidate is elected. For Brazil, Boas et al. (2014) find significant effects of electoral victories on giving contracts to corporate donors.

Despite the limitation of high opacity of data about links between donors and candidates with *Cuentas Claras* database, for including these relationships, I suppose bidirectional links between congressmen of political parties aforementioned and donors of their campaigns in 2018 [27]. After matching names with the same methodology drawn above, I consider only donors that appear registered as CEOs or shareholders in the *Confecámaras* database. A network representation is drawn in Figure 6, where entrepreneurs A and C are donors of congressmen C2 and C3.

[27]Directed links are not drawn because, according to data, it is not possible to know for advance how is the power relationship. As I am interested only in *how* elites are connected to the President and not in hierarchical properties, this can be considered a minor assumption.

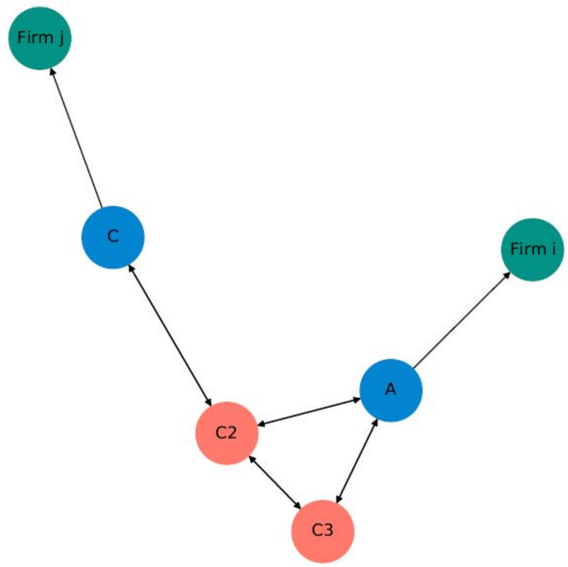


Figure 6: ***Graph representation of Donor - Congressmen relationships.***

Assumption 2.b (Congress members-CEOs links)**.** *Friendship/family relations between CEOs and Congress members for 2018 translated into political connections during the beginning of the COVID-19 pandemic.*

Literature have found that, at firm level, political connections create a buffer against credit downgrades in emerging markets (Jackowicz et al. (2020)), secure greater crisis-period performance (Carney et al. (2020)) and increase benefits derived from emergency measures (Johnson and Mitton (2003)).

Having this empirical support in mind and similar to the procedure with donors, I match the names of persons and firms that appear in *Cuestión Pública* and *La Silla Vacía* datasets with the *Confecámaras* dataset using the same methodology drawn above to uncover relationships between congressmen and firms. Relationships identified are exemplified in Figure 7, containing bidirectional links politician-to-CEO/shareholder and bidirectional links politician-to-firm's-CEOs in case the sole name of a firm appears.

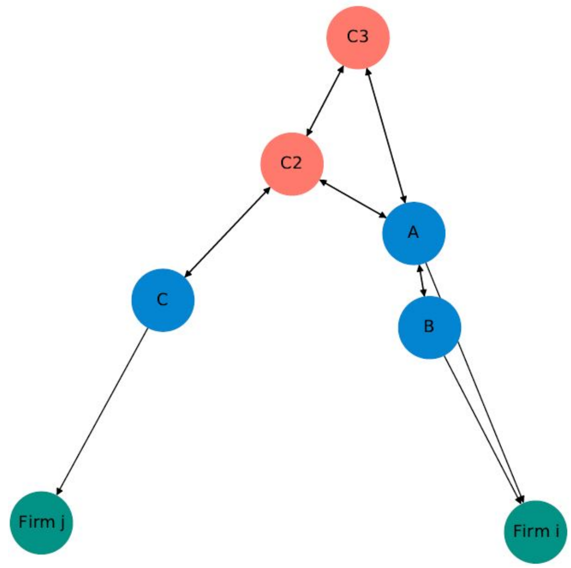


Figure 7: ***Graph representation of CEO - Congressmen relationships.***

From assumptions 2.a and 2.b, thus, I identify politically-connected firms and CEOs/shareholders, capturing an incomplete but reliable map. Moreover, with all three assumptions, I define a *network of political connections* by pooling all networks into one using the same methodology of Natural Language Processing drawn above as I am interested in social connections regardless of its nature. This is a large but necessary simplification as under scenarios of high opacity everything can be taken as a signal and my purpose is not description, the main objective of Padgett and Ansell (1993).

Given this network representation, I estimate how close is a particular firm to the President. For this purpose, I will use again the shortest-path finding algorithm developed by Dijkstra (1959) to calculate the *minimal distance* through links between politically-connected CEOs and the President via donors or friendships relations (D_{CEO}) [28]. While the exact persons that firms might try to attain for government support via political-connections with bounded or complete rationality are impossible to predict quantitatively, we can try to estimate at least a distance (*geodesic distance* in networks literature) measured in positive integers between CEOs of politically-connected firms and the President. As I need to assign to politically non-connected firms a value equal to infinite because there is no connection between them and the President, I define *political closeness* to the President of Colombia as the converse, i.e., $P_{CEO} = 1/D_{CEO}$ and assign politically non-connected firms a value equal to zero as denominator tends to infinite.

[28]The rationale behind Dijkstra algorithm is explained in Appendix F.

4.4 Estimation framework

4.4.1 Treatment/control groups and identification strategy

i. Access to bailouts

The PageRank scores and political closeness to the President are used as continuous treatment variables representing the degree of corporate power/prominence. Due to the opaque nature of ownership/control networks and political power, using these measures based on networks becomes the most suitable path to analyze political-economy factors.

ii. Bailouts Efficiency

Although amounts given to bailed-out firms are not publicly available to make exact estimations, I can still use panel data up to December 2020 for testing ex-post efficiency, being the expenses in salaries and liquidity the outcome variables. The treatment group is the set of firms benefited by PAEF, and the control group is the set of non-bailed out firms with *complete* annual information in outcomes, satisfying eligibility criteria of non-owned by public entities and commercial register before 2020.

As information about eligibility scores is restricted, I will exploit the influence of pre-trends in outcomes for identification. Difference-in-differences (DiD) thus becomes the most suitable framework. As long as I use never-treated units as controls, a baseline sample is not required, but I need to deal with the existence of non-parallel trends as a possible threat. Unfortunately, lack of information makes impossible to deal with possible biases in estimations produced by non-compliance or potential manipulation, so this is a limitation that must be recognized. The non-anticipation assumption is automatically guaranteed as the COVID-19 pandemic was an event impossible to predict for Colombian firms before January 2020.

4.4.2 Empirical Analysis

i. Access to bailouts

To estimate the impact of network prominence/political power of shareholders and CEOs on access, I use cross-section linear-probability regressions to discard the influence of covariates, the same approach of Cruz et al. (2017) and Naidu et al. (2021). This approach is followed as the networked nature of data makes impossible to find external variation sources to make exact identifications (Wagner (1999)) [29], and the information of executives' names is only available for December 2019, so a panel specification is not suitable.

As prominence/economic power is by default a personal attribute but is expressed on firm levels if the person is a member of its Board of Directors, both dimensions (personal and firm levels) must be explored empirically, so two specifications are tested.

As network-prominence measures might be capturing human capital factors (not related to power directly), I use *La Silla Vacía* datasets to estimate a model at CEO/shareholder-levels [30] in the first specification. A significant γ, β or η in the following model signal that political or economic power were significant factors in being benefited after controlling by person-level features:

$$Prob(D_e = 1|X, P, C) = \gamma P_e + \beta C_e + \eta P_e \times C_e + \theta X_e + \tau_s + \epsilon_e, \tag{1}$$

where D_e is a dummy variable equal to one if the PAEF program benefited at least one firm managed by certain shareholder/CEO e; P_e is the PageRank score of the person as a measure of network prominence; C_e is the degree of closeness of certain executive to the President of Colombia. The figure of the President was central because of the two emergency-states declared in Colombia during 2020 that gave him extraordinary powers; X_e is a vector of control variables of nationality,

[29] As Cruz et al. (2020) have remarked, "While we have attempted to account for several potential confounders... we cannot be confident that other unobserved characteristics do not bias our estimates. This is a common limitation of network studies; absent a natural experiment, it is hard to leverage random variation in network characteristics and thus endogeneity is always a concern".

[30] I matched names of *La Silla Vacía* dataset with the *Confecámaras* one by using the same NLP methodology explained above.

gender, age, if is linked to a public entity and education level; τ_e are fixed effects of an industry that each person belongs to; ϵ_e is an identically and independently distributed error term. Errors are standard robust.

Firm-level covariates were crucially important in determining access to the PAEF program, so in the second specification I test the influence of financial factors. For each firm f in industry s and headquartered at municipality m, a significant γ, β or η in the following model signals network prominence, political power of elites or the interaction of both was important in receiving government support through bailouts:

$$Prob(D_{fms} = 1|X, P, C) = \gamma P_f + \beta C_f + \eta P_f \times C_f + \theta X_f + \delta_m + \tau_s + \epsilon_{fms}, \tag{2}$$

where D_{fms} is equal to one if firm f was bailed out under PAEF program during 2020 and 0 otherwise; P_f is the maximum PageRank score across all of its CEOs/shareholders within each firm as a measure of network prominence; C_f is the maximum degree of closeness to the President across all principal members of the company, measuring political connections of firms; X_f is a vector of covariates for each firm f involving size, profitability, liquidity, leverage, firm age (in this specification used as a proxy of riskiness), regulatory quality, efficiency and specific features at levels for December 2019[31], described in Tables 1 and 2. Some covariates are converted to a logarithmic scale to mitigate problems related to outliers; δ_m are municipality-level fixed effects, included because transportation restrictions and internet coverage/quality rates can certainly affect the probability of application in the bailouts program in the context of lockdowns between March and August 2020; τ_s are industry-level fixed effects, added because COVID-19 pandemic affected severely certain industries such as arts, recreation, tourism and transportation but in less degree agriculture, utilities and financial industries [32]; ϵ_{fms} is an identically and independently distributed error term. Errors are standard clustered by municipality and sector [33].

Regarding to number of observations, I define four subsets of covariates depending on availability of data in Tables 1 and 2.

[31]Using information at this point of time, reverse causality concerns are ruled out.

[32]Bancolombia Economic Research Group (2020). "Índice NowCast Bancolombia - Agosto 2020".

[33]All regressions were run in Python and not in Stata, leaving out recent issues.

General feature	Control variable	Description	Dataset
Specific features	Property, plant & equipment on assets	Proportion of assets vital to business operations and non-convertible into cash at short-term, being used as collateral for a loan. Higher values signal a larger buffer in case they need loans to attend emergencies. Used by Faccio et al. (2006).	II, III, IV
Specific Features	Administrative Expenses on Sales	Firms experiencing higher administrative burden faced more problems covering payrolls during pandemic.	II, III, IV
Riskiness	Firm Age	According to Konings and Yergabulova (2021), the pandemic affected younger firms heavily due to financial constraints, uncertainty and lack of reputation. It also controls for transactions centrality of older firms.	I, II, III, IV
Regulatory Quality	Audited	Equal to one if the firm is audited by some regulatory institution. Balance sheets quality and self-reported information factors is addressed.	I, II, III, IV

Table 1: Control variables for specific features, riskiness, information and regulatory quality.

General Feature	Control variable	Description	Dataset
Size	Total operating revenue	Firms with larger revenues generated from primary business activities are more likely to be targeted as they are more likely to support economic recovery by hiring more employees, as it is mentioned in Ministerio de Hacienda (2020b).	I, II, III, IV
Size	Total assets	Following Faccio et al. (2006), large firms in terms of total assets are more likely to play a systemic role in economic performance and may be more likely to receive political attention when confronted with financial distress.	I, II, III, IV
Profitability	Return on assets (ROA) %	Percentage of how profitable a company's assets are in generating revenue.	III, IV
Profitability	Return on equity (ROE) %	Calculated as net income on shareholders' equity.	III, IV
Liquidity	Current ratio	Measures a company's ability to pay short-term obligations or those due within one year, being less needed of government bailouts if they can afford paying its current liabilities with current assets.	I, II, III, IV
Leverage	Debt-on-Assets Ratio	As in Faccio et al. (2006), enterprises with staggering debt before the pandemic are less prone to get access to loans in the middle of the pandemic, becoming more likely to be bailed out.	II, III, IV
Leverage	Assets on equity	Proportion of an entity's assets that has been funded by shareholders.	I, II, III, IV
Efficiency	Total asset turnover	Calculated as total sales on average volume of assets. It is an indicator of efficiency with which a company use its assets to obtain revenue.	IV
Efficiency	Working capital turnover	Calculated as net annual sales on average working capital (current assets minus current liabilities). Measures the efficiency in using current sales and liabilities to support sales.	I, II, III, IV

Table 2: Control variables for size, profitability, liquidity, leverage and efficiency.

Although all firms were considered for calculating network prominence of CEOs, certain were dropped out from descriptive statistics and regressions on the basis they were not eligible to PAEF programs as public-sector entities owned more than 50% of equity [34] or did not have commerical register before 2020.

[34]These firms are *Ecopetrol*, *Interconexión Eléctrica*, *Bolsa Mercantil de Colombia* (BMC), *Grupo de Energía de Bogotá*, *Central de Abastos de Bucaramanga* and *Fondo Ganadero del Tolima*. All public entities supervised by *Contaduría General de la Nación* such as *Empresas Públicas de Medellín* (EPM) were also removed from the sample.

ii. Bailouts efficiency

For testing efficiency, I will analyze if the impacts of the program are heterogeneous in terms of network prominence of CEOs/shareholders, their political closeness to the President, and size-factors using triple-differences (DDD) with annual information from 2017 to 2020.

Ideally, the impacts of the program should be positive as subsiding wages reduces liquidity frictions in the short term and protects employment in the private sector. Using the same notation of Equation 2, I start estimating the following balanced panel regressions with fixed-effects where β is the coefficient of interest, following the specification of Autor et al. (2022b) [35]:

$$S_{fmst} = \alpha + \beta COVID_t \times D_f + \gamma D_f + \delta_{mt} + \tau_{st} + \epsilon_{fmst}, \tag{3}$$

$$L_{fmst} = \alpha + \beta COVID_t \times D_f + \gamma D_f + \delta_{mt} + \tau_{st} + \epsilon_{fmst}, \tag{4}$$

where S_{fmst} is the total amount of expenses in salaries for a firm f headquartered in municipality m, associated to the industry s and with data in December of the year t; L_{fmst} refers to the cash ratio (cash on current liabilities) as a measure of liquidity at the end of each year between 2017 and 2020. Both are expressed in logarithms; $COVID_t$ is a dummy variable equal to 1 for 2020; δ_{mt} and τ_{st} are municipality-year and industry-year fixed-effects, respectively, controlling for time-varying shocks common to firms within a given industry and time-varying shocks common to all firms in a municipality (Autor et al. (2022b)). Both sets of fixed effects are important because industries were affected differently by the pandemic and because municipalities imposed different social distancing rules, so firms may have experienced different degrees of the broader economic downturn. Errors ϵ_{fmst} are clustered by municipality. Observations were weighted by total assets in December 2019.

[35] In this paper, the authors evaluate the impacts of the Paycheck Protection Program (PPP) - a relatively similar program to PAEF - on employment during COVID-19 pandemic, using weekly data of U.S firms. In their specification they cluster errors by sector and not for state. Here I cluster by municipality as the number of economic sectors is not very large.

To analyze heterogeneous effects of the program, I introduce triple differences in the last two equations. Being θ and ν the coefficients of interest, the specifications are rewritten as follows:

$$\begin{aligned} S_{fmst} &= \alpha + \theta COVID_t \times D_f \times M_f + \nu COVID_t \times D_f \\ &+ \xi COVID_t \times M_f + \eta D_f \times M_f + \gamma D_f + \rho M_f + \delta_{mt} + \tau_{st} + \epsilon_{fmst}, \end{aligned} \tag{5}$$

$$\begin{aligned} L_{fmst} &= \alpha + \theta COVID_t \times D_f \times M_f + \nu COVID_t \times D_f \\ &+ \xi COVID_t \times M_f + \eta D_f \times M_f + \gamma D_f + \rho M_f + \delta_{mt} + \tau_{st} + \epsilon_{fmst}, \end{aligned} \tag{6}$$

where M_f refers to potential sources of heterogeneity such as size factors, firm age, the maximum PageRank score among all CEOs/shareholders of each firm and the closeness to the President. All are measured before the pandemic started.

The main trouble with these specifications is the implicit assumption that all firms were benefited in the same months during 2020. Hence, effects might be overestimated as I compare annual balance sheets. The reason is that, according to UGPP Technical Bulletins, the total number of benefited firms decreased, not increased over time. Comparing May 2020 with January 2021, the number of very large firms benefited decreased from 825 to 425 (-48.4%), from 1,238 to 808 large firms (-34.7%), from 5,769 to 3,893 medium-sized firms (-32.5%), from 26.691 to 15.339 small businesses (-42.5%) and 65,704 to 37,172 microenterprises (-43.4%) [36]. This is a drawback that must be recognized.

The main assumption behind my empirical model is that in the absence of PAEF, salaries amounts and liquidity ratios of benefited and non-benefited would have followed a similar trajectory. The validity of this assumption can be partially assessed by estimating the following regression (ϕ_t are dummy variables of years t before the treatment, being 2019 the year of comparison. ϵ_j coefficients must not be significant):

$$S_{fmst} = \alpha + \sum_{t \in T} \epsilon_t (D_f \times \phi_t) + \gamma D_f + \delta_{mt} + \tau_{st} + \epsilon_{fmst}, \tag{7}$$

[36]Bulletins are published in Boletines Técnicos UGPP - PAEF.

$$L_{fmst} = \alpha + \sum_{t \in T} \epsilon_t (D_f \times \phi_t) + \gamma D_f + \delta_{mt} + \tau_{st} + \epsilon_{fmst}, \tag{8}$$

A descriptive analysis of the databases used is presented in Appendix B.

5 Results

5.1 Access to bailouts

In this section, I will present the results of factors that were important in accessing to PAEF program, divided into personal features (CEO-shareholder level) and financial factors (firm level). I find that benefited firms are consistently larger and older across different specifications, but network prominence and political closeness to the President of Colombia were not important factors, signaling a preference for protecting systemically-important firms in terms of employment rather than special interests of economic elites.

Table 3: Effects of CEOs/shareholder prominence and closeness to the President in being bailed out under PAEF during 2020 using personal features

	(1)	(2)	(3)	(4)	(5)	(6)
Pagerank Score	0.27***	0.302***	0.261***	0.266***	0.276***	0.295***
	(0.039)	(0.056)	(0.041)	(0.04)	(0.039)	(0.059)
Closeness to President	-2.511	-1.761	-1.996	-2.315	-2.647	-1.785
	(2.424)	(2.81)	(2.49)	(2.536)	(2.546)	(2.872)
Pagerank Score*Closeness to President	-0.223	-0.164	-0.182	-0.206	-0.233	-0.163
	(0.194)	(0.227)	(0.199)	(0.204)	(0.204)	(0.232)
Public Servant	-0.118					-0.038
	(0.077)					(0.125)
Age		-0.0003				-0.0004
		(0.003)				(0.003)
Nationality			0.051			0.077
			(0.053)			(0.088)
Educational level				-0.003		-0.006
				(0.021)		(0.031)
Gender					0.094	0.047
					(0.057)	(0.098)
Industry FE	✓	✓	✓	✓	✓	✓
Mean-dependent var.	0.497	0.458	0.497	0.509	0.497	0.474
Observations	617	288	617	534	617	270
R-Squared	0.081	0.097	0.079	0.075	0.082	0.104

Notes: Cross-section linear-probability regressions with industry fixed-effects. Confidence intervals are in the parenthesis. Errors are standard robust. *** denotes 1% statistical significance level, ** denotes 2% significance level, and * denotes 5% level. The unit of observation is a CEO or shareholder identified by *La Silla Vacía* as an important entrepreneur.

In Table 3, I present linear-regression results of executive-level factors affecting the probability of receiving PAEF subsidies in at least one of the firms managed in December 2019. Network prominence measured as PageRank score is the only significant variable, while closeness to the President or the interaction is not important. Using personal features exclusively thus, one can conclude that network prominence was important in obtaining PAEF-subsidies.

Marginal effects of size factors, network prominence and being close to the President in the probability of being bailed-out (Equation 2) using firm-level covariates are shown in Tables 4, 5, 6 and 7 with different specifications and datasets aforementioned. Regression results are presented separately as total revenue and total assets as size factors share a significant correlation degree (0.64). Firm age as a feature is included in all regressions as the correlation with total assets and total revenues is low (0.27 and 0.18, respectively).

Table 4: Effects of power factors and Total Revenue in being bailed out under PAEF during 2020

	(1)	(2)	(3)	(4)	(5)
Pagerank Score	-0.089***	-0.089***	-0.101***	0.001	-0.076***
	(0.004)	(0.004)	(0.007)	(0.004)	(0.009)
Closeness to President	0.911*	0.242	0.509	-1.275***	0.008
	(0.44)	(0.406)	(0.319)	(0.314)	(0.291)
Pagerank Score*Closeness to the President	0.081*	0.035	0.055*	-0.091***	0.01
	(0.036)	(0.034)	(0.026)	(0.025)	(0.024)
Total operating revenue		0.083***	0.081***	0.056***	0.059***
		(0.001)	(0.002)	(0.006)	(0.003)
Firm Age		0.028***	0.029***	0.055***	0.051***
		(0.002)	(0.007)	(0.012)	(0.009)
Municipality FE	X	X	✓	X	✓
Industry FE	X	X	X	✓	✓
Covariates	X	✓	✓	✓	✓
Observations	97,120	92,272	92,272	92,272	92,272
R-Squared	0.006	0.121	0.547	0.554	0.559

Notes: Cross-section linear-probability regressions with municipality and industry fixed effects. Controls for size, profitability, liquidity, leverage, riskiness, regulatory quality, efficiency and special factors. Confidence intervals are in the parenthesis. Errors are clustered at municipality and industry levels. *** denotes 1% statistical significance level, ** denotes 2% significance level, and * denotes 5% level. The unit of observation is the firm in each municipality and industry at four digits (CIIU classification).

Table 5: Effects of power factors and Total Revenue in being bailed out under PAEF during 2020

	(1) Dataset I	(2) Dataset II	(3) Dataset III	(4) Dataset IV
PageRank Score	-0.076***	-0.015	-0.015	-0.01
	(0.009)	(0.016)	(0.016)	(0.016)
Closeness to President	0.008	-0.941	-0.941	-1.014
	(0.291)	(0.682)	(0.682)	(0.681)
PageRank Score*Closeness to President	0.01	-0.069	-0.069	-0.076
	(0.024)	(0.056)	(0.056)	(0.056)
Total operating revenue	0.059***	0.028***	0.028***	0.022***
	(0.003)	(0.006)	(0.006)	(0.007)
Firm Age	0.051***	0.052***	0.052***	0.055***
	(0.006)	(0.012)	(0.012)	(0.012)
Municipality FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Municipalities	494	455	418	417
Observations	96,893	45,996	24,052	23,824
R-squared	0.56	0.157	0.16	0.158

Notes: Cross-section linear-probability regressions with municipality and industry fixed effects. Controls for size, profitability, liquidity, leverage, riskiness, regulatory quality, efficiency and special factors. Dataset I contains information of firm age, if the entity is audited, total operating revenue, total assets, current ratio, assets on equity and W.C. turnover. Dataset II adds administrative expenses on sales, debt-on-assets and PE on assets. Dataset III adds ROA and ROE. Dataset IV adds total asset turnover. Confidence intervals are in the parenthesis. Errors are clustered at municipality and industry levels. *** denotes 1% statistical significance level, ** denotes 2% significance level, and * denotes 5% level. The unit of observation is the firm in each municipality and industry at four digits (CIIU classification).

When total revenue is used as size-factor and only financial covariates are considered, the above conclusion changes according to Tables 4 and 5: the correlation between being bailout under PAEF and total revenues becomes positive across different specifications with fixed effects and other variables, at the same time that Network prominence and closeness to President register unstable and not-significant results. This means that systemic-importance factors in terms of protecting employment, rather than defending special interests of elites, seem to be driving access to government bailouts in Colombia during 2020.

Table 6: Effects of power factors and Total Assets in being bailed out under PAEF during 2020

	(1)	(2)	(3)	(4)	(5)
Pagerank Score	-0.089***	-0.091***	-0.105***	-0.024***	-0.069***
	(0.004)	(0.004)	(0.008)	(0.003)	(0.012)
Closeness to President	0.948*	0.085**	1.227***	-0.521	0.214
	(0.435)	(0.036)	(0.446)	(0.355)	(0.333)
Pagerank Score-Closeness	0.084*	0.085**	0.109***	-0.035	0.023
	(0.036)	(0.036)	(0.035)	(0.029)	(0.028)
Total assets		0.003***	0.003	0.004	0.008***
		(0.001)	(0.005)	(0.004)	(0.003)
Firm Age		0.04***	0.044***	0.039***	0.041***
		(0.002)	(0.007)	(0.008)	(0.005)
Municipality FE	X	X	✓	X	✓
Industry FE	X	X	X	✓	✓
Covariates	X	✓	✓	✓	✓
Observations	97,120	92,272	92,272	92,272	92,272
R-Squared	0.006	0.013	0.547	0.554	0.535

Notes: Cross-section linear-probability regressions with municipality and industry fixed effects. Controls for size, profitability, liquidity, leverage, riskiness, regulatory quality, efficiency and special factors. Confidence intervals are in the parenthesis. Errors are clustered at municipality and industry levels. *** denotes 1% statistical significance level, ** denotes 2% significance level, and * denotes 5% level. The unit of observation is the firm in each municipality and industry at four digits (CIIU classification).

Although total revenues and total assets are found to be significantly correlated, the latter does not constitute an important factor driving access according to Tables 6 and 7, reflecting that bailouts were more focused on the ability to generate revenues rather than having large economic resources. Again, firm age is a significant factor, but network prominence and closeness to the President of Colombia are not, suggesting again that pure political-economy factors were not important, and that government bailouts did not seem to contribute to the zombification of the Colombian economy, something that has also been found for other countries such as Italy [37].

[37]Pelosi, M., Rodano, G. Sette, E. (2022). "Zombie firms and the take-up of support measures during COVID-19". The risks of zombification are discussed in Laeven, L., Schepens, G., Schnabel, I. (2020). "Zombification in Europe in times of pandemic".

Table 7: Effects of power factors and Total Assets in being bailed out under PAEF during 2020

	(1) Dataset I	(2) Dataset II	(3) Dataset III	(4) Dataset IV
PageRank Score	0.001	0.001	0.001	0.004
	(0.016)	(0.016)	(0.016)	(0.016)
Closeness to President	-0.894	-0.907	-0.894	-1.002
	(0.71	(0.709)	(0.71)	(0.701)
PageRank Score*Closeness to President	-0.069	-0.07	-0.069	-0.078
	(0.058)	(0.058)	(0.058)	(0.057)
Total assets	-0.006	-0.006	-0.006	-0.006
	(0.005)	(0.005)	(0.005)	(0.005)
Firm Age	0.064***	0.064***	0.064***	0.065***
	(0.009)	(0.005)	(0.009)	(0.009)
Municipality FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Municipalities	494	295	418	190
Observations	96,893	45,996	27,635	7,280
R-squared	0.56	0.157	0.23	0.18

Notes: Cross-section linear-probability regressions with municipality and industry fixed effects. Controls for size, profitability, liquidity, leverage, riskiness, regulatory quality, efficiency and special factors. Dataset I contains information of firm age, if the entity is audited, total operating revenue, total assets, current ratio, assets on equity and W.C. turnover. Dataset II adds administrative expenses on sales, debt-on-assets and PE on assets. Dataset III adds ROA and ROE. Dataset IV adds total asset turnover. Confidence intervals are in the parenthesis. Errors are clustered at municipality and industry levels. *** denotes 1% statistical significance level, ** denotes 2% significance level, and * denotes 5% level. The unit of observation is the firm in each municipality and industry at four digits (CIIU classification).

A possible objection could be that economic elites did not push for getting all firms bailed out but some of them, so conglomerate-level rather firm-level regressions should be a better framework to understand power phenomenas. To address this possibility, I use the ownership/control network described above to estimate *conglomerates* or clusters of firms through the Leiden algorithm proposed by Traag et al. (2019)[38]. Next, financial variables were calculated for each conglomerate by aggregating information of the constituent individual firms [39]. Finally, I estimated Equation 2 with this level of aggregation for datasets I-IV. Results are presented in Table 8. Results does not show different conclusions.

[38]The rationale behind this algorithm is presented in Appendix G.

[39]For each conglomerate, I sum the volume of assets and the total operating revenue for each firm so an aggregate value can be estimated. I calculated mean values of firm age, working capital turnover, current ratio, assets to equity, administrative expenses on sales, debt on assets, PE on assets, ROA/ROE and total asset turnover. Finally, for variables related to economic/political power, I calculated for each conglomerate the largest PageRank score across all of its associated firms, as well the largest closeness to the President across all of its associated firms. Municipality and industry fixed-effects were defined by creating a category for each combination that results from including all firms in one entity.

Table 8: Effects of power factors and Total Revenue in being bailed out at conglomerate-levels

	(1) Dataset I	(2) Dataset II	(3) Dataset III	(4) Dataset IV
Max. PageRank Score	0.007***	-0.006***	-0.006***	-0.007
	(0.001)	(0.002)	(0.002)	(0.002)
Max. Closeness to President	-0.719	-0.654	-0.643	-0.437
	(0.438)	(0.691)	(0.691)	(0.687)
Max. PageRank Score*Max. Closeness to President	-0.055	-0.054	-0.053	-0.036
	(0.037)	(0.058)	(0.058)	(0.058)
Total operating revenue (sum)	0.066***	0.033***	0.033***	0.032***
	(0.001)	(0.003)	(0.003)	(0.003)
Firm Age (mean)	0.03***	0.062***	0.061***	0.061***
	(0.003)	(0.007)	(0.007)	(0.007)
Municipality FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Municipalities	380	303	302	301
Observations	55,880	13,526	13,506	13,458
R-squared	0.614	0.699	0.699	0.699

Notes: Cross-section linear-probability regressions with municipality and industry fixed effects. Controls for size, profitability, liquidity, leverage, riskiness, regulatory quality, efficiency and special factors. Dataset I contains information of firm age, if the entity is audited, total operating revenue, total assets, current ratio, assets on equity and W.C. turnover. Dataset II adds administrative expenses on sales, debt-on-assets and PE on assets. Dataset III adds ROA and ROE. Dataset IV adds total asset turnover. Confidence intervals are in the parenthesis. Errors are clustered at municipality and industry levels. *** denotes 1% statistical significance level, ** denotes 2% significance level, and * denotes 5% level. The unit of observation is the conglomerate (group of firms), identified through the Leiden Algorithm (Traag et al. (2019)).

Although these results seem conclusive, they can still be driven by significant biases even after using fixed effects and financial covariates, as there is no exogenous variation ensuring that these results are more than correlation.

A first concern is related to a likely low quality of control variables: percentages of reduction in operating revenues in the first months of the COVID-19 pandemic are unknown, and covariates might not be useful enough for identification as financial conditions of firms changed significantly due to pandemic. To estimate the magnitude of these possible biases, I check the power of all explanatory variables (measured in December 2019) in predicting if some firm f was a beneficiary of the PAEF program or not through ensemble algorithms. Good predictive power of these machine learning models without fine-tuning parameters (an accuracy/F1-score greater than 70%) would mean this problem is mitigated significantly [40]. This is not a spurious exercise as bailed out firms

[40] Train and test groups of firms were defined randomly through 10 K-Fold cross-validations for robustness to random selections of firms. Ensemble classifiers were used with default parameters of Python's SciKitLearn library.

were larger in total revenues and more leveraged, which signal a higher propensity of receiving support under crisis times (Faccio et al. (2006)). Results are presented in Table 9.

Table 9: Accuracy & F1-Scores of propensity to being bailed out under PAEF

Ensemble Model\Dataset	I	II	III	IV
Random Forests	Ac: 74.62% F1: 71.98%	Ac: 77% F1: 79.99%	Ac: 76.11% F1: 83.33%	Ac: 76.47% F1: 84.91%
Extreme Gradient Boost (X-G. Boosting)	Ac: 70.07% F1: 71.3%	Ac: 73.01% F1: 77.22%	Ac: 73.39% F1: 81.85%	Ac: 74.15% F1: 83.7%
Extremely Randomized Trees	Ac: 73.19% F1: 72.41%	Ac: 75.46% F1: 78.36%	Ac: 73.72% F1: 81.21%	Ac: 75.12% F1: 83.63%
AdaBoost	Ac: 68.2% F1: 68.69%	Ac: 70.2% F1: 74.34%	Ac: 69.54% F1: 79.01%	Ac: 70.25% F1: 81.18%

It can be seen from the table that minimum accuracy and F1 score values (without fine-tuning parameters) are mostly above 70%, meaning that baseline covariates have a significant predictive power of the probability of being beneficiary of the PAEF program during all 2020. This is important to point out because eligibility scores are not publicly available.

As non-linearities of factors behind access to PAEF program might have played a major rol so linear regressions can be a poor tool of analysis, I present complementary analysis using machine learning models that support the main conclusions, presented in Appendix C.

As a problem of omitted variables, there might be an influence of information frictions within municipalities that might affect the results found, making it hard for small firms to participate in the program. As Humphries et al. (2020) have mentioned for the U.S. case, lack of information about the application process and financial illiteracy limited access to government programs for small and medium enterprises during the COVID-19 pandemic. Dealing with this possibility, I perform regressions adding as a control variable the distance between firms with information of latitude/longitude and their nearest bank-branch [41]. Results are presented in Table 10. It can be seen that power-related factors are not significant and total operating revenue still a significant factor, but firm age loose significance.

[41] Although I have access to all headquarters addresses, Python open-source libraries such as *Nominatim* have geocoding limitations for Latin American countries, so the sample is restricted.

Table 10: Effects of power factors and Total Revenue in being bailed out adding nearest-distance to banks as covariate

	(1) Dataset I	(2) Dataset II	(3) Dataset III	(4) Dataset IV
PageRank Score	-0.083***	-0.01	-0.01	-0.007
	(0.011)	(0.022)	(0.022)	(0.022)
Closeness to President	-0.418	-1.765	-1.766	-1.891
	(0.489)	(1.064)	(1.064)	(1.062)
PageRank Score*Closeness to President	-0.025	-0.137	-0.137	-0.148
	(0.04)	(0.086)	(0.086)	(0.086)
Total operating revenue	0.062***	0.035***	0.036***	0.032***
	(0.004)	(0.007)	(0.008)	(0.008)
Firm Age	0.023***	0.01	0.01	0.01
	(0.004)	(0.006)	(0.006)	(0.006)
Municipality FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Municipalities	295	240	240	240
Observations	45,996	12,154	12,154	12,035
R-squared	0.157	0.171	0.171	0.168

Notes: Cross-section linear-probability regressions with municipality and industry fixed effects. Controls for size, profitability, liquidity, leverage, riskiness, regulatory quality, efficiency and special factors. Dataset I contains information of firm age, if the entity is audited, total operating revenue, total assets, current ratio, assets on equity and W.C. turnover. Dataset II adds administrative expenses on sales, debt-on-assets and PE on assets. Dataset III adds ROA and ROE. Dataset IV adds total asset turnover. Confidence intervals are in the parenthesis. Errors are clustered at municipality and industry levels. *** denotes 1% statistical significance level, ** denotes 2% significance level, and * denotes 5% level. The unit of observation is the firm in each municipality and industry at four digits (CIIU classification).

Another potential bias of results comes from measurement errors of network centrality. Robustness checks with similar measures are needed. I will test regressions with eigenvector centrality (Bonacich (1987)) and out-degree centrality (Wasserman and Faust (1994)) as alternative measures, with results presented in Table 11. Again, network prominence as a measure of economic power and closeness to the President of Colombia do not appear to be significant factors in getting access to the PAEF program.

Table 11: Alternative centrality measures - Effects of CEOs/shareholder prominence and closeness to the President in being bailed out under PAEF

	(1)	(2)	(3)
PageRank Score	-0.041***		
	(0.01)		
Eigenvector Centrality		-0.0218***	
		(0.003)	
Out-Degree Centrality			-0.009
			(0.006)
Closeness to President	-0.279	0.242*	-0.552***
	(0.272)	(0.116)	(0.213)
PageRank Score*Closeness to President	-0.017	0.015***	-0.042*
	(0.022)	(0.006)	(0.02)
Observations	92,272	96,814	96,814
R-squared	0.559	0.554	0.554

Notes: Cross-section linear-probability regressions with municipality and industry fixed effects. Controls for size, profitability, liquidity, leverage, riskiness, regulatory quality, efficiency and special factors. Confidence intervals are in the parenthesis. Errors are clustered at municipality and industry levels. *** denotes 1% statistical significance level, ** denotes 2% significance level, and * denotes 5% level. The unit of observation is the firm in each municipality and industry at four digits (CIIU classification).

Another valid criticism is that PageRank scores might indirectly absorb systemic risk factors of Colombian firms in the transactions network, which are not observable and not correlated with the ability to get influence in the corporate world. As financial-networks research has found that size factors are highly correlated with systemic risk metrics (Taleb and Tapiero (2010), Craig and Von Peter (2014), Laeven et al. (2016)), I will examine the correlations between these factors (total assets, operating revenue, and age) and network prominence to explore indirectly an attribution error [42]. Results for the whole sample and the largest 1%-10% firms are presented in Table 12. It can be seen that correlations are low, so this attribution error does not seem to be the case.

Table 12: Cross-section correlations of size-factor covariates with PageRank scores

Covariate\Dataset	I	II	III	IV
Total operating revenue	0.058	0.086	0.118	0.158
Total assets	0.26	0.224	0.274	0.274
Age	-0.04	-0.03	0.018	0.025

Notes: Cross-section cross-correlations.

[42] There is not yet literature of systemic risk in the real sector based on transactions-data according to author's knowledge, so I take this indirect approach.

Regarding to possible selection biases, results could be biased as there are different information sources of financial data. This is important, as only 29,894 firms were supervised by some regulatory institution at 2019 (*Superfinanciera*, *Supersociedades*, etc.), so results could very sensitive. Checking for this possibility, I present in Table 13 regression results per source of information. Bogota C.C., Medellin C.C. and Cali C.C. refer to the chambers of commerce associated to the main cities in Colombia. Although magnitude of coefficients change, significance does not seem to be affected except for results when the sample is restricted to Cali Chamber of Commerce (firm age becomes non-significant), something that can be attributed to the number of observations.

Table 13: Effects of power factors and Total Revenue in being bailed out under PAEF by Source of Information

	(1) Bogota C.C.	(2) Supersociedades	(3) Medellin C.C.	(4) Cali C.C.
PageRank Score	-0.105***	-0.047***	-0.058***	-0.13***
	(0.019)	(0.014)	(0.02)	(0.02)
Closeness to President	0.148	-0.528	-1.636	1.396
	(0.516)	(0.512)	(1.065)	(1.87)
PageRank Score*Closeness to President	0.015	-0.035	-0.123	0.122
	(0.042)	(0.043)	(0.089)	(0.157)
Total operating revenue	0.075***	0.04***	0.078***	0.079***
	(0.004)	(0.006)	(0.008)	(0.005)
Firm Age	0.026***	0.063***	0.022***	-0.004
	(0.007)	(0.009)	(0.009)	(0.009)
Municipality FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Municipalities	100	282	61	7
Observations	44,199	22,922	10,438	7,202
R-squared	0.51	0.16	0.14	0.14

Notes: Cross-section linear-probability regressions with municipality and industry fixed effects. Controls for firm age, if the entity is audited, total operating revenue, total assets, current ratio, assets on equity and W.C. turnover. Errors are clustered at municipality and industry levels. *** denotes 1% statistical significance level, ** denotes 2% significance level, and * denotes 5% level. The unit of observation is the firm in each municipality and industry at four digits (CIIU classification).

Another concern arises from the fact that a few outliers might be driving general results. To analyze this possibility empirically, I divided the whole sample of firms into different quantiles according to the PageRank score calculated, presented in Table 14, running separate regressions with the same main specification but using only firms within a similar interval. It can be seen that PageRank is only significant with a positive sign in the lowest quantile (0%-10%). Closeness to

President and the interaction are not significant factors for all regressions.

Table 14: Effects of CEOs/shareholder prominence and closeness to the President in being bailed out: PageRank Quantiles

Quantile	PageRank	Closeness to President	Interaction	Observations	R-squared
[0%-10%]	0.243*** (0.06)	6.3124 (20.629)	0.4851 (1.567)	11,345	0.185
[10%-20%]	0.4135 (1.27)	750.283 (265.964)	57.4218 (20.351)	907	0.22
[20%-30%]	-0.302*** (0.051)	7.5429 (12.024)	0.5948 (0.928)	21,018	0.137
[30%-40%]	-0.1924 (0.299)	19.211 (32.692)	1.522 (2.574)	30,156	0.541
[40%-80%]	-0.014 (0.076)	-4.197 (11.147)	-0.335 (0.891)	10,503	0.181
[80%-90%]	0.047 (0.089)	1.233 (4.611)	0.107 (0.377)	9,802	0.202
[90%-95%]	-0.017 (0.095)	9.246 (9.419)	0.881 (-1.248,3.01)	5,563	0.18
[95%-99%]	0.0133 (0.052)	1.672 (2.693)	0.153 (0.233)	3,952	0.248
[99%-100%]	-0.052 (0.1)	-3.944 (4.553)	-0.35 (0.413)	825	0.326

Notes: Cross-section linear-probability regressions with municipality and industry fixed effects. Controls for size, profitability, liquidity, leverage, riskiness, regulatory quality, efficiency and special factors. Confidence intervals are in the parenthesis. Errors are clustered at municipality and industry levels. *** denotes 1% statistical significance level, ** denotes 2% significance level, and * denotes 5% level. The unit of observation is the firm in each municipality and industry at four digits (CIIU classification).

For complete robustness, I check if conglomerates of firms associated with the country's wealthiest businessmen benefited more than proportionally under the PAEF program. If economic power factors were important in obtaining government support during the COVID-19 crisis in 2020, one would expect that a significant percentage of firms owned by billionaires or members of their social circle benefited under the PAEF program. For this purpose, I used information of the clusters of firms identified through the Leiden algorithm (as it was explained in Table 8) to identify family-businesses and *keiretsus* of the wealthiest persons of the country, so its feasible to calculate the percentage of benefited firms in each billionaire' conglomerate. Results are presented in Table 15.

Table 15: Percentage of benefited firms under PAEF in Colombian billionaires' conglomerates

Billionaire (Forbes Colombia 2020 list)	Number of firms in his conglomerate	Number of bailed out firms	Percentage
Luis Carlos Sarmiento Angulo	166	31	18.67%
Jaime Gilinski Bacal	59	9	15.25%
Alejandro Santo Domingo Dávila	57	14	24.56%
Carlos Ardila Lülle	69	26	37.68%
Cortes-Osorio Brothers	68	5	7.35%
Mario Pacheco Cortés	49	11	22.44%
Eduardo Pacheco Cortés	66	6	9.09%
Echavarría-Olázaga Family	59	21	35.59%
Manuel Santiago Mejía	29	3	10.34%
Carlos Alberto Solarte	44	10	10.72%
Char-Abdala Family	113	24	21.23%
Pedro Felipe Carvajal	75	11	14.66%
Francisco Barberi Ospina	38	3	7.89%
Vegalara Family	53	11	20.75%
Mesa-Diez Family (Grupo Bios)	30	4	13.33%

From the Table it can be seen that, apart from Carlos Ardila Lülle and Echavarría-Olázaga Family (who received a coverage larger than 30% under PAEF program), none of these conglomerates seem over-benefited under PAEF program, confirming that economic power was not an important factor.

In sum, these results suggest that age and total operating revenues, not the prominence of CEOs or their political-connections, were important factors positively correlated in getting access to the PAEF program during 2020. Instead of defending special interests, it can be argued that the program's focus seems to be on protecting systemic-important firms in terms of employment to secure economic recovery.

5.2 Bailouts efficiency

Despite the fact that the effects of the program are robustly positive, I do not find evidence that the largest firms in terms of revenues or older registered larger effects in salaries and liquidity than smaller/medium businesses by the end of 2020. These results suggest that the program had a desirable effect on the Colombian economy, but there were no ex-post economic gains of prioritizing older and large firms (in terms of total revenues) so its focus was not correct.

Before explaining the main results of estimations, I will start presenting checks for parallel-trends and a comparative table showing that I use a sufficiently large number of firms to make comparisons between treated and control units.

Results for parallel trends for salaries and cash-ratio as outcomes are presented in Figure 8, which show ϵ_t coefficients obtained from the estimation of equations 7 and 8. The black x-axis line in 2019, the reference period for the parallel-trends regression, divides the years before and with the treatment. Point estimates are presented as well as their 95% confidence intervals. In both cases, prior to 2020, coefficients are statistically not different from zero, indicating the absence of differential trends in outcomes before the COVID-19 pandemic and thus, giving credibility to the parallel trends assumption.

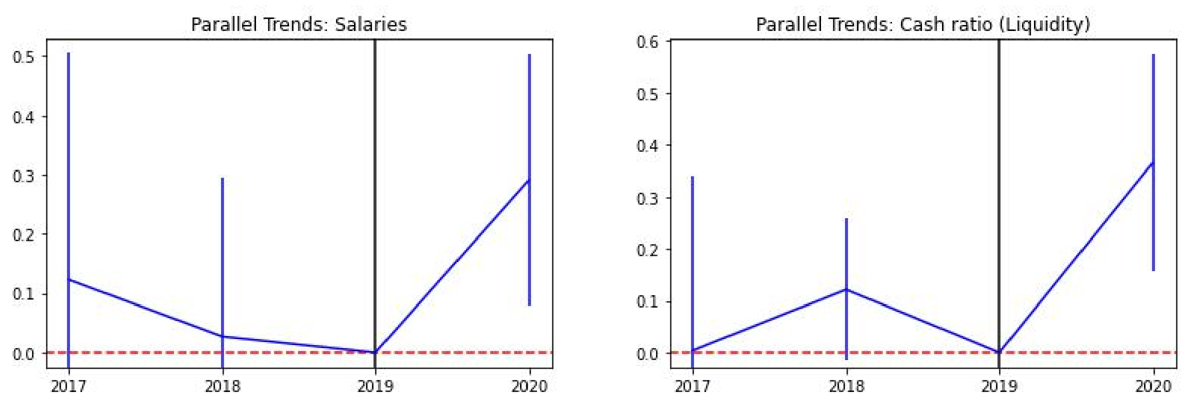


Figure 8: Parallel Trends validation assumption

A possible threat for estimating heterogeneous effects would be the fact that treated firms are highly concentrated on the highest quantiles of the distribution of the total revenues at the same time small/medium businesses are heavily concentrated in the lowest ones or some combination.

As a result, one could not compare firms to make valid inferences due to an implied mismatching problem. Dealing with this possibility, I calculated 20%, 40%, 60%, and 80% quantile values of the distribution of total revenues, firm age and PageRank with the dataset I (containing 96,893 observations) I used in the last section to classify the firms analyzed here into different groups, checking if the imbalance is high. Results are presented in Tables 16, 17 18. For each outcome and quantile of total revenues and firm age, I calculate the number of treated and control firms and the percentage they represent of the total sum of firms. For total revenues, the mismatching only arises in the 0%-20% percentile for the cash ratio (controls constitute the 80.51% and treated firms the 19.48%). The imbalance is less pronounced in the other quantiles. For firm age and PageRank scores, the percentage of treated units does not exceed 70% in all quantiles, showing more balanced distributions.

Table 16: Number of treated/control firms by quantile of Total Operating Revenues

Quantile\ Treatment Status	Salaries		Cash Ratio (Liquidity)	
	Non-Benefited (Controls)	Benefited (Treated)	Non-Benefited (Controls)	Benefited (Treated)
[0%-20%]	61 (48.03%)	66 (51.96%)	686 (80.51%)	166 (19.48%)
[20%-40%]	121 (37.93%)	198 (62.06%)	561 (64.93%)	303 (35.06%)
[40%-60%]	161 (36.01%)	286 (63.98%)	548 (54.85%)	451 (45.14%)
[60%-80%]	270 (33.79%)	529 (66.2%)	738 (41.74%)	1,030 (58.25%)
[80%-100%]	1,032 (32.74%)	2,120 (67.25%)	2,643 (33.83%)	5,169 (66.16%)

Table 17: Number of treated/control firms by quantile of Firm Age

Quantile\ Treatment Status	Salaries		Cash Ratio (Liquidity)	
	Non-Benefited (Controls)	Benefited (Treated)	Non-Benefited (Controls)	Benefited (Treated)
[0%-20%]	75 (33.48%)	149 (66.51%)	216 (45%)	264 (55%)
[20%-40%]	243 (42.04%)	335 (57.95%)	649 (51.5%)	611 (48.49%)
[40%-60%]	329 (35.41%)	600 (64.58%)	948 (44.86%)	1,165 (55.13%)
[60%-80%]	370 (34.29%)	709 (65.7%)	1,087 (39.96%)	1,633 (60.03%)
[80%-100%]	628 (30.87%)	1,406 (69.12%)	2,278 (35.24%)	3,446 (64.75%)

Table 18: Number of treated/control firms by quantile of PageRank

Quantile\ Treatment Status	Salaries		Cash Ratio (Liquidity)	
	Non-Benefited (Controls)	Benefited (Treated)	Non-Benefited (Controls)	Benefited (Treated)
[0%-20%]	274 (36.68%)	473 (63.31%)	891 (47.52%)	984 (52.48%)
[20%-40%]	241 (37.42%)	403 (62.57%)	673 (41.11%)	964 (58.88%)
[40%-60%]	0 (0%)	0 (0%)	0 (0%)	0 (0%)
[60%-80%]	294 (33.29%)	589 (66.7%)	1,008 (41.8%)	1,403 (58.19%)
[80%-100%]	457 (35.59%)	827 (64.4%)	1,593 (43.84%)	2,040 (56.15%)

Results of estimating main equations 3, 4, 5 and 6 are presented in Tables 19 and 20, where $COVID$ refers to a dummy variable equal to one for information at the end of 2020, $PAEF$ is the participation variable, $PageRank$ refers to the maximum-PageRank score across all Board of Directors of each firm at the end of 2019 (three months prior to the pandemic) and other variables (Closeness to the President, Firm Age, Total operating revenue) refer to their literal meaning. In the first column of each table I present the estimated values of β for equations 3 and 4 in the row associated to $COVID{*}PAEF$. From the second to the last column I show the estimated coefficients of ν of equations 5 and 6 in the row associated to $COVID * PAEF$, and the estimated coefficients for θ in the next rows depending on the potential source of heterogeneity.

Table 19: Effects of PAEF program on salaries

	(1)	(2)	(3)	(4)	(5)
COVID*PAEF	0.243***	-2.387	0.29***	0.234	-0.017
	(0.089)	(1.908)	(0.091)	(0.477)	(0.21)
COVID*PAEF*PageRank		-0.187			
		(0.148)			
COVID*PAEF*Closeness to President			-1.815		
			(1.281)		
COVID*PAEF*Firm Age				-0.082	
				(0.163)	
COVID*PAEF*Total operating revenue					-0.03
					(0.022)
Industry-Year FE	✓	✓	✓	✓	✓
Municipality-Year FE	✓	✓	✓	✓	✓
Mean dep. var.	896.01	896.01	896.01	896.01	896.01
Firms	4,844	4,844	4,844	4,844	4,844
Treated Firms (%)	66.04%	66.04%	66.04%	66.04%	66.04%
Observations	19,376	19,376	19,376	19,376	19,376
R-squared (General)	0.005	0.021	0.029	0.047	0.527

Notes: Balanced panels estimated with industry-year and municipality-year fixed-effects. Outcome variables are expressed in logarithms to deal with outliers. Standard errors are in the parenthesis. Errors are clustered at municipality levels. *** denotes 1% statistical significance level, ** denotes 2% significance level, and * denotes 5% level. The unit of observation is the firm in each municipality and industry at four digits (CIIU classification). Observations are weighted by total assets in December 2019.

The first interaction ($COVID * PAEF$) in the first row suggests that the program had strong positive effects for the end of 2020, maintaining higher the total expenses in salaries in 24.3% and the cash ratio in 32.9% in average compared to non-bailed out firms. Although the number of employees is not available in the dataset to measure the impact more directly, the magnitude of these effects reveals that PAEF successfully protected the real sector from systemic risks created by the COVID-19 pandemic.

On the other hand, the non-significance of the coefficients associated with triple interactions $COVID * PAEF * PageRank$ and $COVID * PAEF * ClosenesstoPresident$ in Equations 5 and 6 in salaries, suggests that bailed out firms run by prominent economic elites did not experiment greater effects of the program compared to bailed out firms run by non-prominent executives. However, the PageRank score (although not the closeness to the President) is a significant source of heterogeneity for liquidity: the cash ratio is maintained higher in 34.5% in firms with average PageRank (-12.58, as this is measured in logarithms). This implies that the main effect on benefited firms run by powerful economic elites was on liquidity instead of employment.

Table 20: Effects of PAEF program on liquidity

	(1)	(2)	(3)	(4)	(5)
COVID*PAEF	0.329***	3.98**	0.304***	-0.156	-0.243
	(0.105)	(1.55)	(0.106)	(0.546)	(0.494)
COVID*PAEF*PageRank		0.345***			
		(0.122)			
COVID*PAEF*Closeness to President			-0.164		
			(0.766)		
COVID*PAEF*Firm Age				-0.05	
				(0.169)	
COVID*PAEF*Total operating revenue					-0.005
					(0.052)
Industry-Year FE	✓	✓	✓	✓	✓
Municipality-Year FE	✓	✓	✓	✓	✓
Mean dep. var.	0.154	0.154	0.154	0.154	0.154
Firms	12,298	12,298	12,298	12,298	12,298
Treated Firms (%)	57.88%	57.88%	57.88%	57.88%	57.88%
Observations	49,189	49,189	49,189	49,189	49,189
R-squared (General)	0.011	0.023	0.012	0.023	0.038

Notes: Balanced panels estimated with industry-year and municipality-year fixed-effects. Outcome variables are expressed in logarithms to deal with outliers. Standard errors are in the parenthesis. Errors are clustered at municipality levels. *** denotes 1% statistical significance level, ** denotes 2% significance level, and * denotes 5% level. The unit of observation is the firm in each municipality and industry at four digits (CIIU classification). Observations are weighted by total assets in December 2019.

Finally, the effects are null for both outcomes when using age and total revenues ($COVID * PAEF * FirmAge$, $COVID * PAEF * TotalOperatingRevenues$) as a possible source of heterogeneous effects. This means there were no ex-post economic gains from prioritizing certain firms that played a systemic role in terms of economic recovery, despite these factors were important in getting access to the program as it was discussed before. These findings are confirmed for another study of the effects of the PAEF program (Baena (2022)) using the number of employees and the survival rates as outcome variables [43]. This might explain why the focus of the program changed in 2021 under 2155 Law, where small-businesses were targeted to boost employment.

To check the robustness of results to the inclusion of fixed-effects for equations 3, 4, 5 and 6, I present results with different specifications in Tables 21 and 22. The significance of the effects of the program described above is maintained except for the main effects on liquidity when industry-year fixed-effects are omitted, meaning that COVID-19 pandemic affected diferentially the liquidity of

[43] The author depicts an even more problematic story, as she concludes that ”the fall in employment was stronger in the large and very large companies with PAEF than in non-beneficiaries”. Limitations of information that the author also had are addressed here by using other datasets.

each industry so these time-varying factors are crucial for identification. The heterogeneous effects of corporate power in liquidity but not in employment is robust to inclusion of fixed-effects according to Table 22, showing again the indirect effect of the program on firms directed by powerful elites: an increase in one percent of PageRank score, previous to COVID pandemic, maintained higher the cash ratio additionally in 38.4% and 46.4% in firms with average PageRank when industry-year or municipality-year fixed effects are omitted, respectively.

Table 21: Robustness to fixed-effects specifications (DiD)

	(1) Salaries	(2) Salaries	(3) Salaries	(4) Cash Ratio	(5) Cash Ratio	(6) Cash Ratio
COVID*PAEF	0.243***	0.329***	0.202***	0.329***	0.292***	0.238
	(0.089)	(0.114)	(0.085)	(0.105)	(0.112)	(0.195)
Industry-Year FE	✓	✓	X	✓	✓	X
Municipality-Year FE	✓	X	✓	✓	X	✓
Mean dep. var.	896.01	896.01	896.01	0.154	0.154	0.154
Firms	4,844	4,844	4,844	12,298	12,298	12,298
Treated Firms (%)	66.04%	66.04%	66.04%	57.88%	57.88%	57.88%
Observations	19,376	19,376	19,376	49,189	49,189	49,189

Notes: Balanced panels estimated with industry-year and municipality-year fixed-effects. Outcome variables are expressed in logarithms to deal with outliers. Standard errors are in the parenthesis. Errors are clustered at municipality levels. *** denotes 1% statistical significance level, ** denotes 2% significance level, and * denotes 5% level. The unit of observation is the firm in each municipality and industry at four digits (CIIU classification). Observations are weighted by total assets in December 2019.

Table 22: Robustness to fixed-effects specifications (Triple differences)

		(1) Salaries	(2) Salaries	(3) Salaries	(4) Cash Ratio	(5) Cash Ratio	(6) Cash Ratio
PageRank	COVID*PAEF	-2.387	-3.24	0.87	3.98**	4.429***	5.429***
		(1.908)	(1.656)	(1.11)	(1.55)	(1.202)	(1.88)
	COVID*PAEF*PageRank	-0.1876	-0.258	0.089	0.345***	0.384***	0.464***
		(0.148)	(0.13)	(0.086)	(0.122)	(0.096)	(0.145)
Closeness to President	COVID*PAEF	0.29	0.365***	0.246***	0.304***	-0.212	-0.558
		(0.091)	(0.119)	(0.079)	(0.106)	(0.530)	(0.815)
	COVID*PAEF*Closeness to President	-1.815	-1.55	-1.721	-0.164	-0.047	0.081
		(1.281)	(1.138)	(1.241)	(0.766)	(0.161)	(0.248)
Firm Age	COVID*PAEF	0.234	0.332	-0.111	-0.156	-0.212	-0.558
		(0.477)	(0.477)	(0.396)	(0.546)	(0.53)	(0.815)
	COVID*PAEF*Firm Age	-0.082	-0.098	-0.045	-0.05	-0.047	0.081
		(0.163)	(0.163)	(0.127)	(0.169)	(0.161)	(0.248)
Total operating revenue	COVID*PAEF	-0.017	0.087	-0.157	-0.243	-0.612	-0.754
		(0.21)	(0.239)	(0.188)	(0.494)	(0.352)	(0.736)
	COVID*PAEF*Total operating revenue	-0.03	-0.04	-0.024	-0.005	0.028	0.039
		(0.022)	(0.027)	(0.019)	(0.052)	(0.041)	(0.083)
	Industry-Year FE	✓	✓	X	✓	✓	X
	Municipality-Year FE	✓	X	✓	✓	X	✓
	Mean dep. var.	896.01	896.01	896.01	0.154	0.154	0.154
	Firms	4,844	4,844	4,844	12,298	12,298	12,298
	Treated Firms (%)	66.04%	66.04%	66.04%	57.88%	57.88%	57.88%
	Observations	19,376	19,376	19,376	49,189	49,189	49,189

Notes: Balanced panels estimated with industry-year and municipality-year fixed-effects. Outcome variables are expressed in logarithms to deal with outliers. Standard errors are in the parenthesis. Errors are clustered at municipality levels. *** denotes 1% statistical significance level, ** denotes 2% significance level, and * denotes 5% level. The unit of observation is the firm in each municipality and industry at four digits (CIIU classification). Observations are weighted by total assets in December 2019.

One of the main shortcomings of results relies on the large confidence intervals estimated. Trying to explain what might be driving this result, I will explore the differential effects for each industry and the asymmetry of weights given to observations as possible reasons. I find that this last possibility, and not the first one, explains the standard errors estimated for coefficients.

Checking the first possibility, I estimated again Equations 5 and 6 but defining dummy variables of industry as source of heterogeneity. Significant values would signal differential effects of PAEF program in units belonging to a certain category compared to not belonging to. Results are presented in Table 23. Regarding to salaries, it can be seen that lower effects are registered only for firms in commerce. As the specification controls for common shocks within industries or municipalities but not for individual unobserved factors, benefited firms were likely in the edge of bankruptcy during 2020 so impacts on this sector were significantly lower. In liquidity there are not major differences by sector after dropping firms whose ratio exceeds 5 for some year [44]. This homogeneity in impacts across industries is intelligible as PAEF program did not give more benefits to some special industry according to 677 Decree. More aids to highly-damaged industries were contemplated only from the end of 2020 under 2162 Resolution.

Table 23: Heterogeneous effects of PAEF program on salaries and liquidity by sector

Outcome\ Economic Sector	Salaries		Cash Ratio (Liquidity)	
	COVID*PAEF	COVID*PAEF*Sector	COVID*PAEF	COVID*PAEF*Sector
Agriculture	0.252*** (0.092)	0.557 (0.6073)	0.317*** (0.11)	-0.529 (0.313)
Mining	0.242*** (0.089)	-0.12 (0.0902)	0.302*** (0.105)	0.143 (0.619)
Manufacturing	0.249** (0.105)	-0.295 (0.3622)	0.241 (0.132)	0.21 (0.262)
Electricity & Gas	0.238*** (0.092)	3.433*** (0.88)	0.302*** (0.114)	-0.129 (0.202)
Water	0.244*** (0.089)	0.281 (0.3436)	0.305*** (0.108)	-0.048 (0.804)
Construction	0.245** (0.097)	0.4611 (0.889)	0.365*** (0.117)	-0.396 (0.276)
Commerce	0.229* (0.114)	-0.757*** (0.2139)	0.33*** (0.127)	-0.148 (0.21)
Transportation	0.28*** (0.103)	1.084 (1.609)	0.297*** (0.112)	0.211 (0.194)
Acc. & Food Services	0.268*** (0.077)	0.292 (0.707)	0.313*** (0.11)	-0.114 (0.471)
Information & Communications	0.253*** (0.091)	-0.216 (0.195)	0.289** (0.113)	0.395 (0.345)
Financial	0.237*** (0.086)	0.979 (0.218)	0.311*** (0.101)	-0.58 (0.923)
Real Estate	0.218*** (0.082)	-0.25 (0.313)	0.306*** (0.111)	-0.039 (0.273)
Professional Services	0.25*** (0.092)	-0.018 (0.941)	0.311 (0.111)	-0.203 (0.303)
Education	0.245*** (0.089)	-0.808 (0.474)	0.305*** (0.109)	0.174 (0.23)
Healthcare	0.15*** (0.083)	-0.302 (0.28)	0.311*** (0.109)	-0.468 (0.279)
Arts & Recreation	0.247*** (0.09)	0.381 (0.837)	0.302*** (0.109)	1.271 (0.702)
Mean dep. var.	896.01	896.01	0.122	0.122
Firms	4,844	4,844	11,323	11,323
Treated firms (%)	66.04%	66.04%	60.25%	60.25%
Observations	19,376	19,376	45,289	45,289

Notes: Balanced panels estimated with industry-year and municipality-year fixed-effects. Outcome variables are expressed in logarithms to deal with outliers. Standard errors are in the parenthesis. Errors are clustered at municipality levels. *** denotes 1% statistical significance level, ** denotes 2% significance level, and * denotes 5% level. The unit of observation is the firm in each municipality and industry at four digits (CIIU classification). Observations are weighted by total assets in December 2019.

[44] When the 49,189 observations are included, the large jumps that small firms registered made the results unreliable at the estimated values for θ were highly negative. Trying to deal with this problem, I instead present results with this modification only in this table.

Exploring the second possibility, as observations were weighted by total assets in 2019, I sorted the firms according the assets volume and split the whole sample into five approximately-equal groups, estimating in each one Equations 3 and 4. As the largest firms are reallocated into one group (80%-100% quintile), estimated standard errors in the first groups should be lower as observations are more equally weighted. Results are presented in Tables 24 and 25, showing that this is certainly the case for both outcomes: larger standard errors are found for the 80%-100% quantile. Interestingly, the effect is positive only for the first quantile for salaries, but for liquidity the effect is increasingly positive and significant across different quantiles analyzed.

Table 24: Effects of PAEF program on salaries by quintiles of Total Assets in December 2019

	(1) 0%-20%	(2) 20%-40%	(3) 40%-60%	(4) 60%-80%	(5) 80%-100%
COVID*PAEF	0.201*** (0.04)	0.11 (0.062)	0.004 (0.054)	0.043 (0.058)	-0.043 (0.135)
Industry-Year FE	✓	✓	✓	✓	✓
Municipality-Year FE	✓	✓	✓	✓	✓
Mean dep. var.	227.10	607.273	833.375	1274.50	3935.107
Treated Firms (%)	73.47%	71.10%	66.11%	63.67%	55.88%
Observations	3,876	3,876	3,872	3,875	3,872

Notes: Balanced panels estimated with industry-year and municipality-year fixed-effects. Outcome variables are expressed in logarithms to deal with outliers. Standard errors are in the parenthesis. Errors are clustered at municipality levels. *** denotes 1% statistical significance level, ** denotes 2% significance level, and * denotes 5% level. The unit of observation is the firm in each municipality and industry at four digits (CIIU classification). Observations are weighted by total assets in December 2019.

Table 25: Effects of PAEF program on liquidity quintiles of Total Assets in December 2019

	(1) 0%-20%	(2) 20%-40%	(3) 40%-60%	(4) 60%-80%	(5) 80%-100%
COVID*PAEF	0.257**	0.363***	0.432***	0.497***	0.507***
	(0.1)	(0.043)	(0.051)	(0.054)	(0.129)
Industry-Year FE	✓	✓	✓	✓	✓
Municipality-Year FE	✓	✓	✓	✓	✓
Mean dep. var.	0.222	0.19	0.168	0.142	0.115
Treated Firms (%)	56.91%	61.65%	60%	58.27%	52.7%
Observations	9,839	9,835	9,840	9,835	9,836

Notes: Balanced panels estimated with industry-year and municipality-year fixed-effects. Outcome variables are expressed in logarithms to deal with outliers. Standard errors are in the parenthesis. Errors are clustered at municipality levels. *** denotes 1% statistical significance level, ** denotes 2% significance level, and * denotes 5% level. The unit of observation is the firm in each municipality and industry at four digits (CIIU classification). Observations are weighted by total assets in December 2019.

Testing for the sensitivity of results to outliers, I perform different regressions excluding a percentage of the largest firms in terms of assets volume. Top 1, 2, 3, 4, 5 and 10 percentages are considered. Results are presented in Tables 26 and 27, showing that main results hold until the 4% of the largest firms are excluded. For 5% and 10%, the coefficients seem to be significantly different.

Table 26: Effects of PAEF program on salaries without outliers (dropping out largest firms)

	(1) 1%	(2) 2%	(3) 3%	(4) 4%	(5) 5%	(6) 10%
COVID*PAEF	0.232**	0.212***	0.282***	0.257***	0.287***	0.464***
	(0.096)	(0.066)	(0.105)	(0.058)	(0.111)	(0.115)
Industry-Year FE	✓	✓	✓	✓	✓	✓
Municipality-Year FE	✓	✓	✓	✓	✓	✓
Mean dep. var.	896.51	888.026	885.73	880.489	873.84	867.91
Treated Firms (%)	66.02%	65.92%	65.85%	65.54%	65.45%	65.40%
Observations	19,172	18,988	18,794	18,600	18,407	17,438

Notes: Balanced panels estimated with industry-year and municipality-year fixed-effects. Outcome variables are expressed in logarithms to deal with outliers. Standard errors are in the parenthesis. Errors are clustered at municipality levels. *** denotes 1% statistical significance level, ** denotes 2% significance level, and * denotes 5% level. The unit of observation is the firm in each municipality and industry at four digits (CIIU classification). Observations are weighted by total assets in December 2019.

Table 27: Effects of PAEF program on liquidity without outliers (dropping out largest firms)

	(1) 1%	(2) 2%	(3) 3%	(4) 4%	(5) 5%	(6) 10%
COVID*PAEF	0.294***	0.385***	0.275***	0.31***	0.462***	0.506***
	(0.081)	(0.088)	(0.076)	(0.084)	(0.07)	(0.076)
Industry-Year FE	✓	✓	✓	✓	✓	✓
Municipality-Year FE	✓	✓	✓	✓	✓	✓
Mean dep. var.	0.163	0.163	0.163	0.163	0.163	0.163
Treated Firms (%)	60.1%	59.8%	59.6%	57.2%	58.6%	55.1%
Observations	48,697	48,205	47,713	47,221	46,279	44,270
R-squared	0.007	0.008	0.0211	0.0226	0.0206	0.012

Notes: Balanced panels estimated with industry-year and municipality-year fixed-effects. Outcome variables are expressed in logarithms to deal with outliers. Standard errors are in the parenthesis. Errors are clustered at municipality levels. *** denotes 1% statistical significance level, ** denotes 2% significance level, and * denotes 5% level. The unit of observation is the firm in each municipality and industry at four digits (CIIU classification). Observations are weighted by total assets in December 2019.

6 Conclusions

Using a novel dataset of 189,000+ enterprises, I study whether the prominence of CEOs as a measure of economic power or size factors was important to firms getting access to the PAEF program during 2020. Furthermore, I analyze if the program was effective and if these power factors affected the efficiency of the program. Findings can be summarized as follows:

(i) There is no evidence supporting that the political power of firms was correlated with the

probability of being bailed out during 2020. Being close to the President of the Republic of Colombia or his circle of officialist politicians was not a significant factor in being bailed out during the COVID-19 crisis.
(ii) Being run by prominent CEOs and shareholders was not positively correlated with the probability of being bailed out during 2020. Instead, total operating revenues and firm age were positively correlated factors, suggesting a preference for protecting systemically-important firms in terms of employment rather than special interests of economic elites.
(iii) PAEF program had strong positive effects on firms in terms of salaries and liquidity. PAEF program helped to protect, on average, 24.3% the amount of expenses in salaries and in 32.9% the cash ratio as a measure of liquidity during the pandemic when comparing benefited vs. non-benefited firms. Thus, it can be concluded that the program was effective in helping firms to survive and securing a fast macroeconomic recovery. However, firm age and total operating revenue do not appear to be sources of heterogeneity of effects, signaling that large-sized or older firms did not over-perform small or young firms, hence that the focus of the program did not yield extraordinary results and thereby the allocation of public resources was not correct ex-post. These general findings have been also found for Baena (2022) regarding to PAEF program, using the number of employees and survival rates as outcome variables.

It is important to understand the limitations of the quantitative approaches followed: (a) it is assumed that two or more persons cannot share a complete name of a CEO/shareholder; (b) all executives are assumed to exercise their power equally within each firm; (c) only annual balance sheets from 2017 were used; (d) firms are assumed to start being bailed out with the same amounts and at the same time when measuring efficiency of bailouts; (e) there is no public information on the amounts of subsidies delivered to each firm or information on the benefited firms in each month; (f) there is no public information of firms in the control group that were closed to be benefited.

Methodological contributions are direct, as complex networks and Natural Language Processing approaches are followed. The reconstruction of ownership and control network structures can be used to understand political-science topics such as the influence of CEOs on democratic elections, the influence of family-groups/dynasties on the Congress, the political-economy of tax-cuts or regulatory measures and other complex-phenomenas in the future.

7 Conflicts of Interest

The author declares no conflict of interests in the elaboration of this document. There is no funding or any relationship with some government, business association, or political party.

8 Appendices

Appendix A Job Titles of Boards of Directors

Administrative Director, Administrative Manager, Administrative Vicepresident, Administrative and Financial Manager, Administrator, Alternate Legal Representative, Chief Executive Officer, Chief Financial Officer, Commercial Director, Commercial Manager, Commercial Vicepresident, Commercial and Marketing Director, Controller, Deputy General Manager, Deputy Member of the Board of Directors, Deputy Member of the Management Board, Director, Executive Director, Financial Manager, Financial Vicepresident, Financial and Administrative Director, General Manager, Head of Budget, Head of Internal Control, Honorary President, Legal Representative, Legal Vice President, Manager, Member of the Board of Directors, Member of the Executive Committee, Member of the Management Board, President, President of the Board of Directors, Substitute Director, Treasurer, Vice President, Vice President of the Board of Directors, Vicemanager.

Appendix B Descriptive Analysis

In this appendix, a descriptive analysis for treatment variables and baseline covariates is presented. Industries more affected by the pandemic registered higher percentages of coverage. Bailed out firms in distribution exhibit more efficiency, liquidity and leverage; are bigger, older and, at least for the largest firms, their board of directors did not have more prominence than non bailed out firms for December 2019 (three months before the pandemic started).

B.1 Bailouts

In terms of coverage, descriptive statistics suggest a focus on the most affected industries. Number and percentage of firms receiving bailouts under PAEF program from the total sample by type of dataset (defined above) is presented in Table 28. In each cell of the table, number of total firms is registered in the upper and the number of benefited firms in the lower part, followed by the corresponding percentage. An analysis of the column (I) is presented as it contains the largest sample of firms.

Industry	I	II	III	IV
Agriculture	3,880 1,345 (34,6%)	1,383 549 (39,6%)	522 245 (46,9%)	385 187 (48,5%)
Mining	809 359 (44,3%)	354 180 (50,8%)	128 74 (57,8%)	112 63 (56,2%)
Manufacturing	11,786 7,745 (65,7%)	3,509 2,368 (67,4%)	1,737 1,192 (68,6%)	1,705 1,178 (69%)
Electricity & Gas	200 64 (32%)	33 13 (39,3%)	22 6 (27,2%)	20 4 (20%)
Water	446 195 (43,7%)	47 26 (55,5%)	13 10 (76,9%)	11 9 (81,8%)
Construction	15,537 6,447 (51,4%)	3,347 2,134 (63,7%)	1,136 860 (75,7%)	993 773 (77,8%)
Commerce	21,598 12,469 (57,6%)	5,976 4,123 (68,9%)	2,209 1,595 (72,2%)	2,161 1,568 (72,5%)
Transportation	4,893 2,768 (56,5%)	511 326 (63,7%)	189 127 (67,1%)	105 76 (72,3%)
Accomodation & Food Services	1,849 1,225 (66,2%)	396 318 (80,3%)	169 139 (82,2%)	146 123 (84,2%)
Information & Communications	3,634 1,650 (45,4%)	689 354 (51,3%)	271 151 (55,7%)	170 107 (62,9%)
Financial	9,315 1,752 (18,8%)	3,884 704 (18,1%)	386 111 (28,7%)	72 25 (34,7%)
Real Estate	10,164 2,265 (22,2%)	2,626 792 (30,1%)	477 202 (42,3%)	143 79 (55,2%)
Professional Services	10,928 4,967 (45,5%)	1,426 780 (52,1%)	436 269 (63,9%)	209 154 (73,6%)
Education	965 576 (59,6%)	148 105 (70,9%)	45 39 (86,6%)	14 12 (85,7%)
Healthcare	5,313 3,224 (60,6%)	3,903 2,568 (65,7%)	41 25 (60,9%)	26 20 (76,9%)
Arts & Recreation	804 452 (56,2%)	134 91 (67,9%)	55 44 (80%)	38 31 (81,5%)

Table 28: Bailouts coverage by industry and number of firms.

Food Services, Manufacturing and Healthcare were the main covered industries under the PAEF program, with more than 60% of large firms benefiting as a proportion of the total sample, reflecting that this program was intended to help enterprises severely damaged by the pandemic. Real Estate (22.2%) and utilities - Water (43,7%), Electricity (32%) - industries were not significantly benefited given lockdowns and travel restrictions from March to August 2020 did not affect public services provision.

It is important to highlight that firms of the financial sector were excluded mainly (only 18.8% received the benefit, primarily financial cooperatives). Regulation by national entities exercised strict controls with capital buffers, and the Central Bank provided liquidity to capital markets, adopting special measures as the credit channel for small and medium-sized enterprises dried up

[45].

One would have expected, however, a more extensive coverage for Arts & Recreation firms (56,2% were bailed out), as tourism and cultural activities were banned suddenly to contain the spread so they were more affected than any other industry.

B.2 Financial Factors

To analyze differences in financial baseline covariates between PAEF and non-PAEF benefited firms (up to December 2019), I compare correspondent distributions with two-sample Kolmogorov-Smirnov (KS) tests, in which the alternative hypothesis is bailed out firms under the PAEF program register higher values than non bailed out firms in distribution for certain covariate [46]. P-values of the test for each industry and covariate are shown in Figures 9 and 10. For each covariate, I use the largest dataset in which is available (I, II, III or IV) to establish the largest comparisons as is possible.

As stated in Figure 9, bailed out firms are bigger in terms of operating revenue and total assets in almost all industries, an expected result as large firms hire more employees with a formal contract, the objective of the program. In terms of efficiency, targeted firms were consistently more efficient than non-bailed out firms for most industries before the pandemic started, in terms of total sales on every unit of working capital [47]. Regarding leverage, except for Electricity and Gas and Public Administration industries [48], bailed out firms registered more debt as a proportion of assets and assets as a proportion of equity. This observation holds for debt as a proportion of assets, except for financial, education, and food services industries. Finally, analyzing differences in current industries, the ones with the largest number of firms registered more liquidity capacity measured as current assets on short-term liabilities.

[45] Banco de la República (2020). "¿Qué ha hecho el Banco de la República para enfrentar el impacto de la pandemia en la economía?".

[46] I do not assay equality of distributions as my focus is to find special characteristics of targeted firms.

[47] This is consistent with the observation in Figure 10 that targeted firms have larger administrative burdens as a percentage of net sales for Manufacturing and Commerce industries.

[48] This industry is composed of firms working with public projects, not the public sector per se.

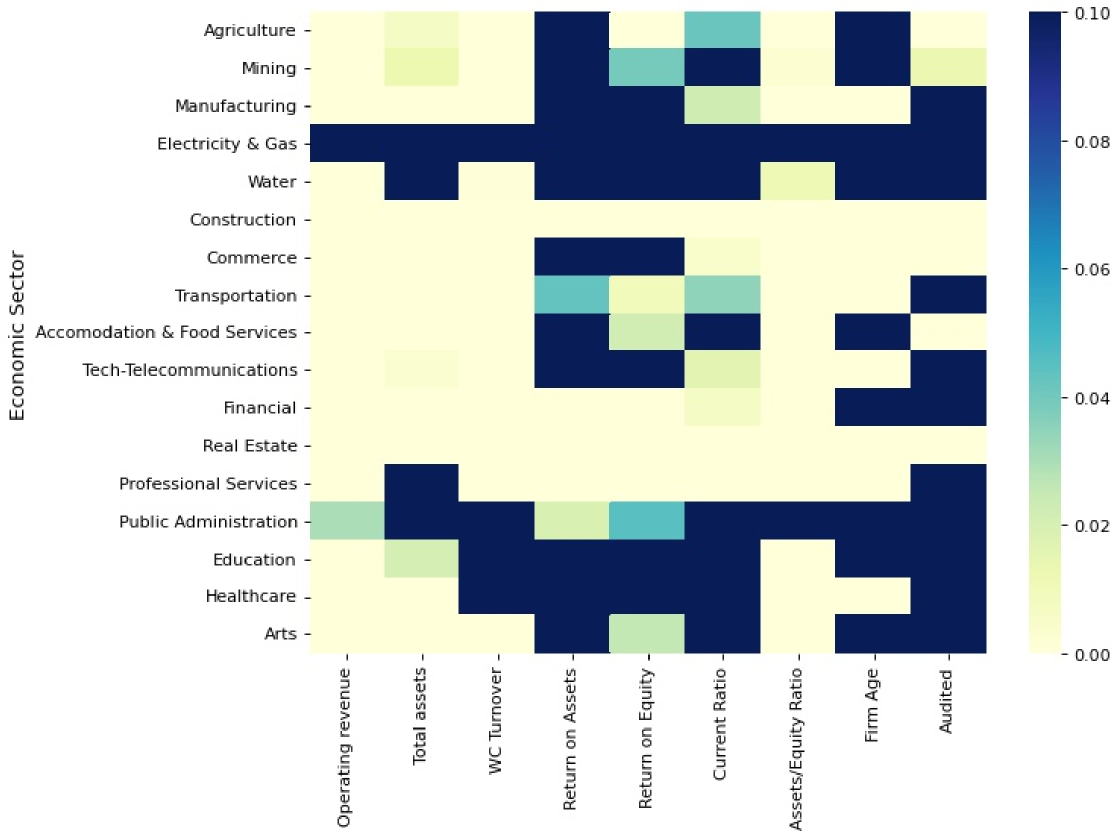


Figure 9: *P-values of Kolmogorov-Smirnov tests for differences (Ha: PAEF firms are larger).*

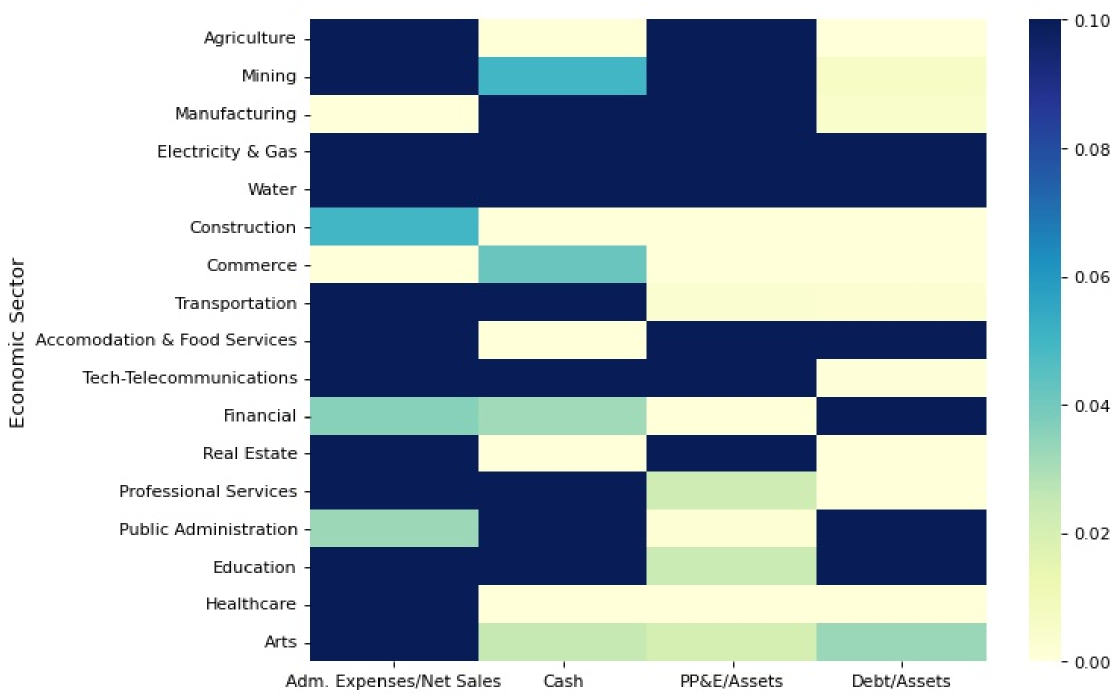


Figure 10: *P-values of Kolmogorov-Smirnov tests for differences (Ha: PAEF firms are larger).*

More sparse results are found regarding profitability. While returns on assets or equity are larger in Construction, Financial, Real Estate and Professional Services industries, there are not significant differences in Commerce, Manufacturing, Technology Telecommunications, Healthcare or Agriculture.

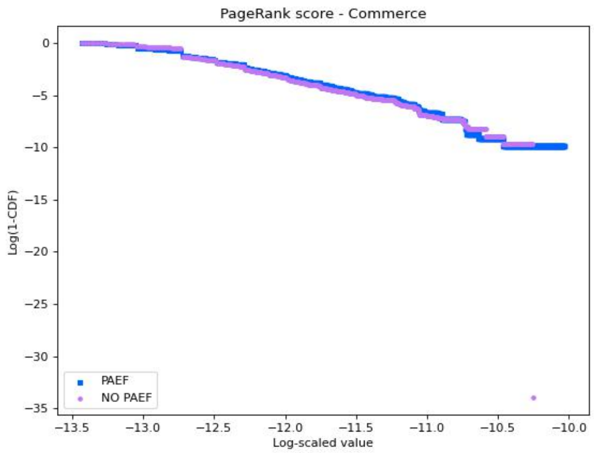
Finally, regarding to age, targeted firms are significantly older in Construction, Commerce, Transportation, Technology/Telecommunications, Real Estate, Professional Services and Healthcare. This is controversial as younger firms were more affected by COVID-19 crisis (Konings and Yergabulova (2021)), but did not receive special support.

These findings suggest that most bailed-out firms are larger and older than the non-benefited ones, performed better before the pandemic in efficiency and liquidity but worse in leverage, and are more fragile to extreme events. In terms of profitability, results are mixed.

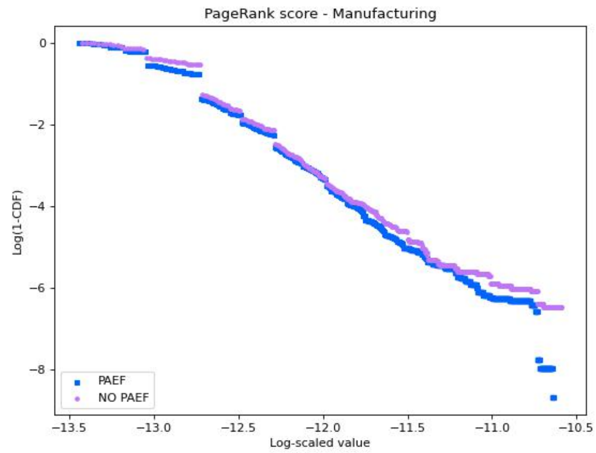
B.3 Network Prominence

Overall, firms that benefited by PAEF program have CEOs and shareholders who did not register higher network prominence than non-benefited firms. Figures 11 and 12, that compare graphically the cumulative distribution of PageRank scores between benefited and non-benefited firms for different industries, suggest economic power in the form of network prominence was not crucial in getting access to bailouts.

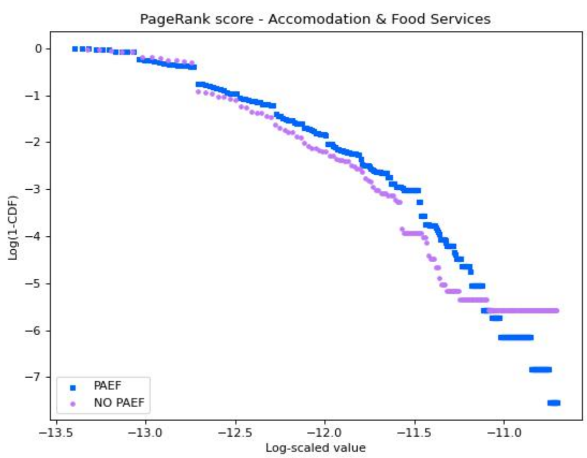
In these figures, following the statistical approach of Glattfelder and Battiston (2009), the value in the logarithm of PageRank (axis X) is plotted jointly with the logarithm of the complement of the cumulative distribution function (axis Y), so distributions with a high number of observations in the right tails decay slower than less concentrated distributions. Because distributions of bailed out firms (colored in blue) are located below or overlap the distributions of non bailed out firms (in magenta) for most graphs, we can say CEOs or shareholders of the first group do not exhibit more considerable prominence than the second group in a certain industry.



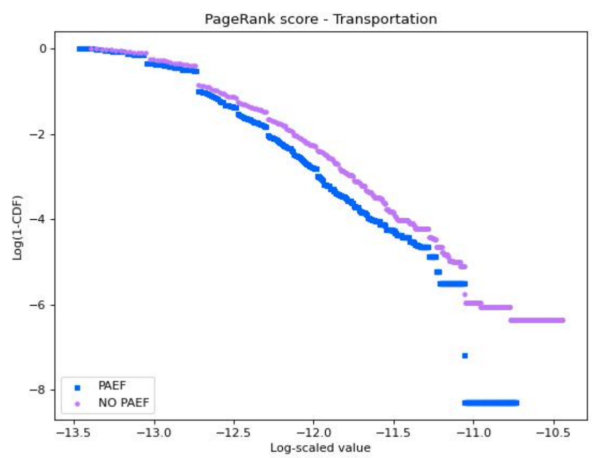
(a) Commerce



(b) Manufacturing



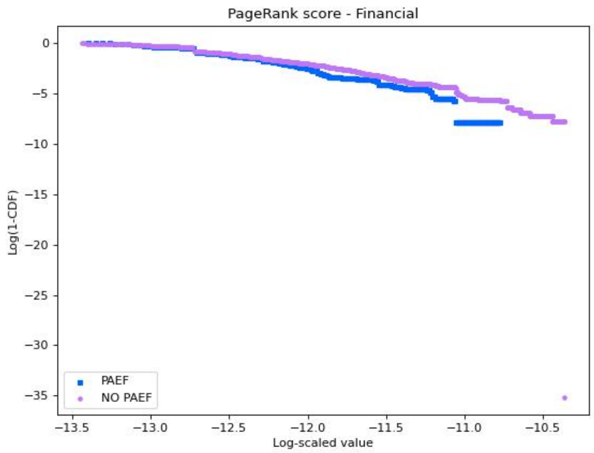
(c) Accomodation & Food Services



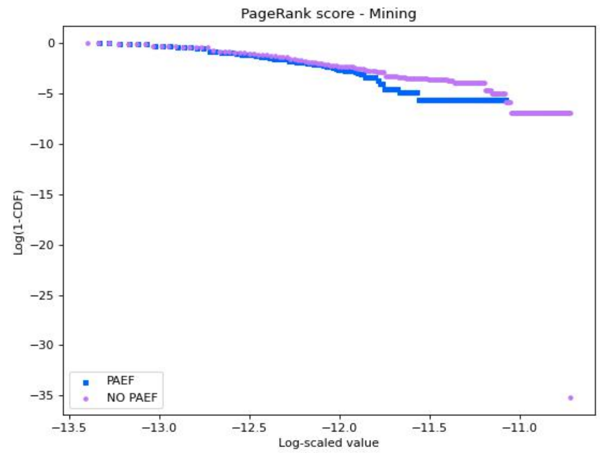
(d) Transportation

Figure 11: PageRank cumulative distributions for industries with large differences

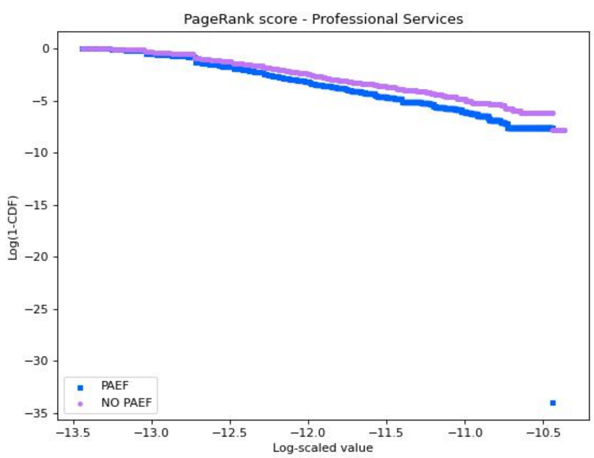
All in all, this suggests that economic power was not an important factor in receiving PAEF subsidies, despite large-sized and older firms were given more importance they play a systemic role in terms of the number of employees. Disentangling each of these factors quantitatively, in a more causality-oriented way, is the center of interest of this paper, with results presented below.



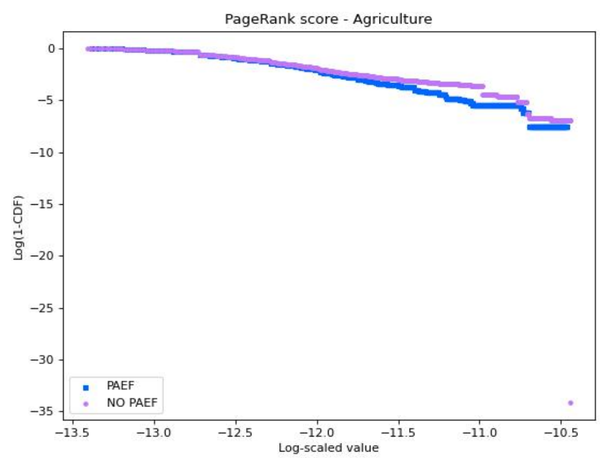
(a) Financial



(b) Mining



(c) Professional Services



(d) Agriculture

Figure 12: PageRank cumulative distributions for industries with small differences

B.4 Politically connected and unconnected firms

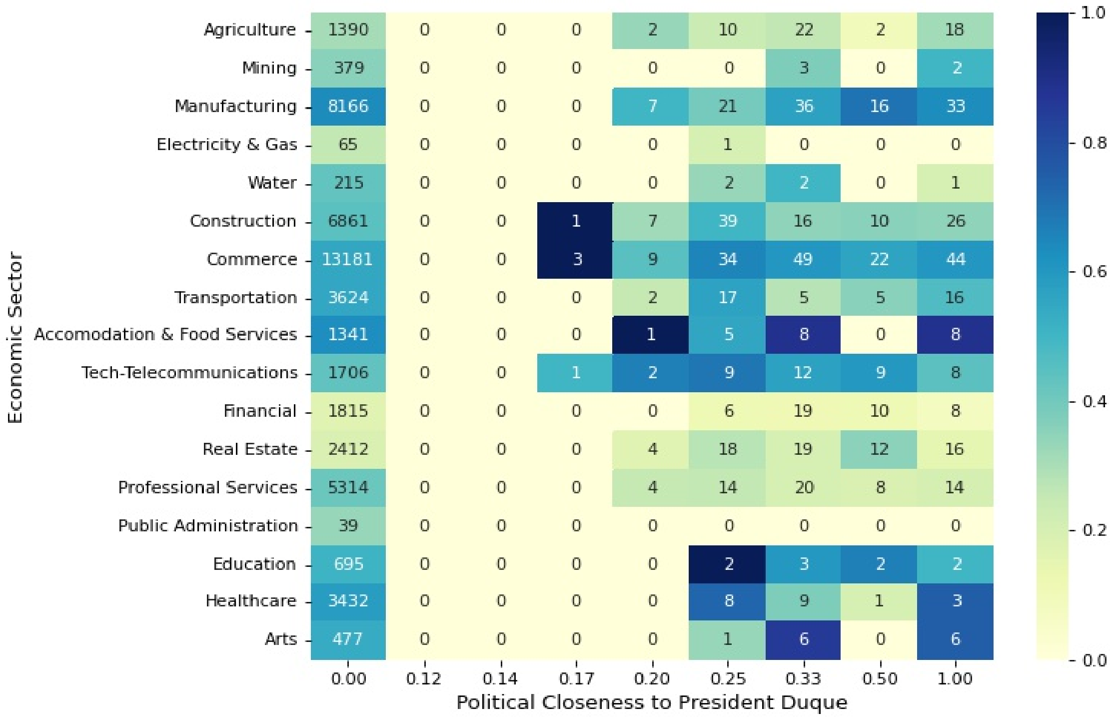


Figure 13: ***Number & percentage of bailed out firms by industry and closeness to President of Colombia.***

Firms close to the President did not benefit more proportionally than politically non-connected firms under the bailouts program. In Figure 13, I present for each industry the number of bailed-out firms according to its *closeness* to the President (numbers in each cell) and the percentage they represent of the total number of politically-connected firms (colors in each cell). Ideally, increasing values from left to right would signal that political-connections were an important factor, but it can be seen that this is not the case at all.

This arguably makes sense as there was no Congress involvement in designing and approving emergency measures. Therefore, corruption or direct influence from politicians' channels in trying to access the program seems to not exist in this case.

Appendix C Decision Tree: Propensity to being bailed out

For completeness of the analysis, in this appendix I describe the results obtained by training a random-forest model to model the probability of being bailed-out under PAEF program, which is a binary vector. This exercise is done as robustness to results obtained with linear regressions with fixed-effects.

The random-forest model was trained using information up to 2019, using all covariates associated to Dataset I, ROA, ROE and dummy variables of municipality/industry. Information of 94,630 firms was used. To calibrate the model, grid search was used over a hyperparameter search-space [49]. Despite large limitations of information, the ability to predict ahead of time which firm was bailed out was surprisingly good, obtaining a ROC AUC of 72.1, according to Figure 14.

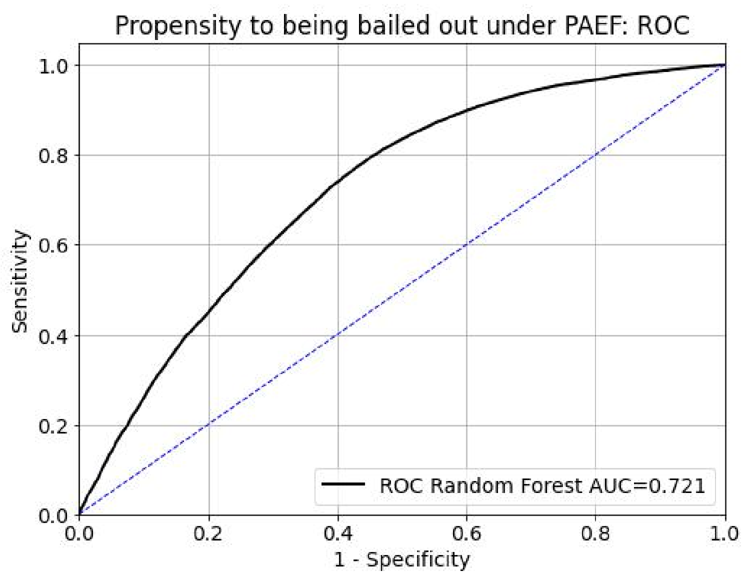


Figure 14: ***ROC curve.***

In order to understand which factors were actually important, a decision-tree with the optimized hyperparameters was estimated, presented in Figure 15.

[49]The hyperparameter search-space was defined as follows: minimum number of samples in each leaf: 7, 21, 31, 50; max-depth: 5, 7, 10, 13; number of trees: 10, 50, 100, 500

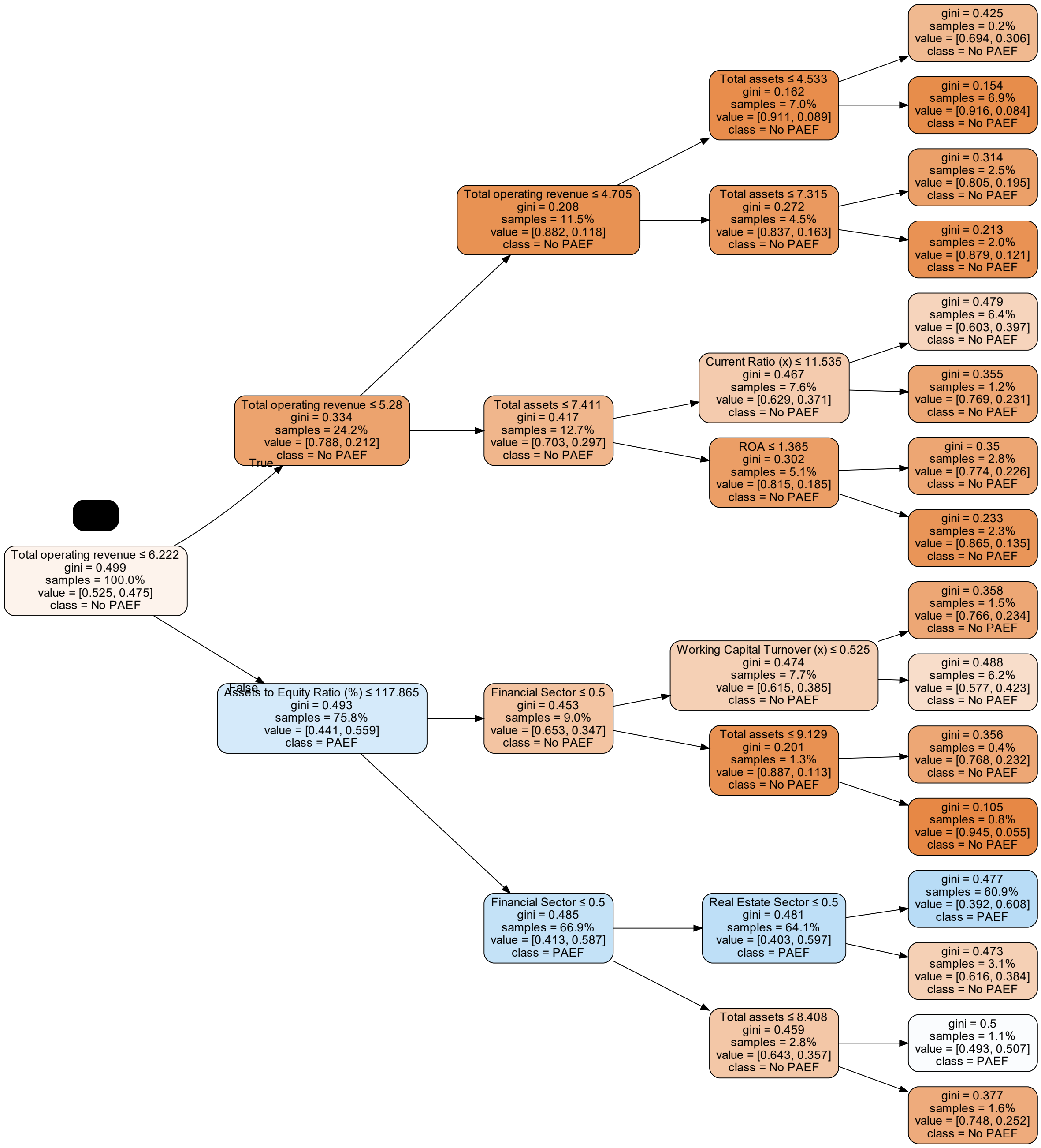


Figure 15: ***Decision tree - Propensity to being bailed out under PAEF program in 2020.***

This graph can be used to understand which factors were truly influential in deciding which company received government support or not during 2020, as a tree of conditions emerges from patterns found in the data. Arrows going up indicate what happens if the condition is satisfied, arrows going down indicate what happens if not. It can be seen thus that the first deciding factor was the firm size, as firms with more than 502 millions of pesos in total revenue (its logarithm is

6.222) were much more likely to get coverage (firm age might not appear as important as might not be as good discriminator as total revenue). The second factor is leverage, as firms with a ratio larger than 117.86% (very leveraged before 2020), received a more special support. A final factor of interest seem to be the industry, as firms not associated to financial/real estate sectors received much more support, something consistent with the differential effects of the pandemic by industry. These results confirm findings shown in the main part of the document.

Appendix D Ratcliff-Obershelp Algorithm

In order to determine which pairs of names $S1$ and $S2$ constitute a duplicate, in this paper I use as a first similarity-measure the Ratcliff-Obershelp Algorithm, based on the ratio of the number of matching characters (K_m) between these two strings and the total number of both strings ($\mid S1 \mid + \mid S2 \mid$):

$$S_{ro} = \frac{2K_m}{\mid S1 \mid + \mid S2 \mid}, 0 \leq S_{ro} \leq 1$$

The number of matching characters is calculated as the longest common substring and the matching characters of the non-matched sides of this longest substring.

As an example, let suppose that $S1$ and $S2$ are defined as $S1 =$ 'JULIO MARIO SANTODOMINGO PUMAREJO' (33 characters) and $S2 =$ 'JULIO M SANTODOMINGO' (20 characters), refering to a Colombian-American billionaire businessman. The longest common substring is "SANTODOMINGO" (12 characters), and the non-matching substring at the left side is 'JULIO M' (7 characters). Therefore, $K_m = 12 + 7 = 19$ and $\mid S1 \mid + \mid S2 \mid = 53$, hence $S_{ro} = 0.7169$.

Appendix E Network Ranking Measures

Out-Degree Centrality:

Let A the matrix of dimensions n x n with cells $a_{f,n}$ representing the adjacency matrix drawn in the main text, representing a directed-unweighted graph (an asymmetric and binary matrix, by definition). In each row, certain firm or executive n exercises a control/ownership as CEO/shareholder on a set of firms f. The out-degree is defined as the sum of nodes its outgoing edges are connected to, i.e.,

$$OutDegree_n = \sum_f a_{f,n}$$

Degree centrality gives a simple count of the number of firms (natural/non-natural) that a person exercises control on.

Eigenvector Centrality:

Eigenvector centrality is used in this document to measure the level of influence of a CEO/shareholder (acting as *nodes*) within the network of ownership and control. Each CEO/shareholder within the network is given a score or value: the higher the score the greater the level of prestige/ownership within the network. This score is relative to the number of connections a CEO/shareholder will have to other nodes (natural/non-natural firms) in form of ownership/control relationships. Connections to high-scoring eigenvector centrality nodes contribute more to the score of the node than equal connections to low-scoring nodes, that is, connections to firms who are themselves influential will lend a person more influence than connections to less influential firms.

Mathematically, this level of influence is captured in the dominant eigenvector of the adjacency matrix $A = (a_{v,t})$ for a given graph $G := (V, E)$ for all $|V|$ node. In this matrix, $a_{v,t} = 1$ if node v exercise a control/ownership on a node t, and 0 otherwise. The eigenvector centrality of node v is calculated as

$$x_v = \frac{1}{\lambda} \sum_{t \in M(v)} a_{v,t} x_t,$$

where $M(v)$ is the set of firms (natural/non-natural figures) in which v exercises power/control and λ is a constant equal to the largest eigenvalue of the matrix A.

In a vector notation, the vector x representing centrality can be obtained from the equation

$$Ax = \lambda x$$

By the Perron-Frobenius Theorem, there exist only one eigenvector x (dominant vector) with non-negative elements and whose sum is equal to one that satisfies this last equation, constituting the centrality measure that is used in this paper.

PageRank Score:

The PageRank score is a variant of the eigenvector centrality, calculated through an algorithm proposed by Brin and Page (1998). For each node i of the network; $M(P_i)$ firms (natural/non-natural) managed by this node; and $L(P_j)$ entities/persons that exercise control/ownership on each firm j managed by i, the PageRank score of the node i is calculated as

$$PageRank_i = \frac{1-\theta}{N} + \theta \sum_{j \in M(P_i)} \frac{PageRank_j}{L(P_j)},$$

where N is the number nodes in the network and θ is a damping factor between zero and one (in this case is equalized to 0.85), representing the probability that, in this case, an imaginary CEO/executive who is randomly following links of ownership/control to exercise power will eventually stop doing that. The algorithm supposes the existence, in this case, of powerful people facing a trade-off of two options in the attempt to exercise her/his power in the corporate world: (a) following a strategy of owning/being CEO of firms randomly (the first term); (b) using their current position in the network to get much influence as possible (the second term). The balance between both options is represented in the last equation.

To calculate PageRank scores for each node i a iterative procedure is followed, defining in the iteration $t = 0$ an initialization value equal to $\frac{1}{N}$ and then, in the next iterations, computing the formula above, depending on the structural position of i for $t+1$ regarding to the other j-th nodes in t:

$$PageRank_i(0) = \frac{1}{N}$$
$$PageRank_i(t+1) = \frac{1-\theta}{N} + \theta \sum_{j \in M(P_i)} \frac{PageRank_j(t)}{L(P_j)}$$

Matricially, the calculation of the PageRank score vector is defined equivalently as follows. Let

w a vector of binary values of dimension N, equal to one if certain node cannot control/own any other firm and 0 otherwise; 1^T an $1 * N$ vector of elements equal to one; A the adjacency matrix defined in the main text; θ the damping factor and R a matrix of order N with all elements equal to $\frac{1}{N}$. The vector of PageRank scores p is defined as the vector satisfying

$$pG = p, G = \theta(A + \frac{1}{N}w1^T) + (1 - \theta)R$$

This means that p is the eigenvector associated to a stochastic matrix G and an eigenvalue equal to 1. This vector is unique because, as G is an stochastic matrix, i.e, G has no negative values and the sum of elements of its rows is equal to 1, by the Perron-Frobenius Theorem, the eigenvalue equal to 1 is the dominant eigenvalue of G and his geometric multiplicity is equal to 1.

Appendix F Dijkstra Algorithm

To understand the rationale behind this algorithm, is important to define the elements first. Let $G = (V, A)$ a simple graph with V as the set of vertices representing politicians, members of congress or Boards of Directors of some firm and A the set of edges or links identified. A shortest path between certain s vertex (*source vertex*, in the graph theory literature) and some other vertex (*target vertex*), identified by v, is defined a $d(v)$. S is a set of visited vertices, already examined by the algorithm. $p(v)$ is the predecessor of vertex v in the algorithm, given $v \neq s$. Finally, $w(s, v)$ is defined as the weight between a pair of vertices s and v, which is simplified to 1 in this paper because political networks are defined here as unweighted due to lack of information.

To initialize the algorithm, $d(s)$ is set to zero by definition. Furthermore, for each vertex v adjacent from s, $d(v) = w((s, v))$ and $p(v) = s$; ∀v: v $\neq s$ not adjacent to s, $d(v) = +\infty$ and S is defined as $\{s\}$ at this stage.

The internal functioning of the algorithm goes as follows: (1) For all elements in V different from S, find v such that $d(v)$ is minimized; (2) For all vertex u adjacent from v, calculate $d(u)$ and $n = d(v) + w((v, u))$. If $d(u) < n$, define $d(u) = n$ and $p(u) = v$; (3) S is redefined as $S \bigcup \{v\}$; (4) If $S = V$, the procedure is stopped. Otherwise, repeat (1).

Appendix G Leiden Community-Detection Algorithm

Before explaining the algorithm, I will define the elements and mathematical notation, following the technical appendix of Traag et al. (2019). Let $G = (V, E)$ a graph with V as the set of n vertices or nodes, and E as the set of edges. The purpose of the algorithm, as it is stated in the main text, is to partition the graph G into several disjoint groups of nodes (communities), so we have a partition $P = C_1, C_2, ..., C_r$, $C_i \subseteq V$, $V = \bigcup C_i$, $C_i \bigcap C_j \neq \emptyset$.

There are two definitions of graphs used. G is defined as a *base graph*, G' as a graph that can be a new graph, and its nodes are communities of the partition P of the graph G, i.e., $V(G') = P$. $E(G')$ is a set of multiedges such that $E(G') = [(C, D)|(u, v) \in E(G), u \in C \in P, v \in D \in P]$. $P' = [v]$

$\mathcal{H}(G, P)$ is a function that maximise *quality* of the partition P of the graph G. In this paper, the Constant Potts Model quality function (CPM function) was used, defined as $\mathcal{H}(G, P) = \sum_{C \in P}[E(C, C) - \gamma\binom{\|C\|}{2}]$ and representing a sum along each community C, where $\|C\|$ is the number of elements in C, $E(C, D) = |[(u, v) \in E(G)|u \in C, v \in D]|$ is the number of edges between nodes of community C and nodes of community D, and γ is a *resolution parameter* that is equal to 0.005 in this paper, meaning that communities should have a density of at least 0.005, while the density between communities should be lower than 0.005 [50]. $P(v \longmapsto C)$ represents the partition (set of communities) obtained when a node v moves to a community C. $\Delta\mathcal{H}(v \longmapsto C) = \mathcal{H}(v \longmapsto C) - \mathcal{H}(P)$ refers to the change in quality after moving v to C; $\Delta\mathcal{H}(S \longmapsto C)$ refers to the change in quality after moving a group of nodes S to C.

With these elements in mind, the algorithm works as follows.

1. Moving nodes phase. Let Q a queue, defined as set of nodes that will be visited. The algorithm starts considering each node of the graph as a single community and then merging them iteratively into different communities of different sizes. For each node v from Q, a community C' is selected such that $C' = \mathrm{ArgMax}_{c \in P \cup \emptyset} \Delta\mathcal{H}(v \longmapsto C)$. If $\Delta\mathcal{H}(v \longmapsto C) > 0$, node v is assigned to C', the set N of neighbors of node v that are not part of C' are identified, and they are put in the queue set Q, so $Q = Q \cup (N \setminus Q)$. This task is repeated until $Q = \emptyset$.

[50] Higher resolutions lead to more communities and lower resolutions lead to fewer communities.

2. Refinement phase at node level. The partition P is refined in a way such that different communities are identified within each community S, integrated by nodes or subsets of nodes C (defined by a previous iteration of the algorithm). First, a set of nodes R is defined as the set of nodes such that, for each node v of S, $E(v, S \setminus v) \geq \gamma \|v\|.(\|S\| - \|v\|)$. This means what only well-connected nodes within S are selected, as the number of edges between v and $S \setminus v$ is higher than a threshold that depends on the difference in the number of elements between S and v. Next, in case v is in a singleton community, join it to a subset of nodes C' within S. Each of the possible communities to join has to be well-connected $(E(C, S \setminus C) \geq \gamma \|C\|.(\|S\| - \|C\|))$, and the criteria for joining to a specific community C' and not another one is that the probability to joining to community C' is maximal among all communities C, calculated as $Exp(\frac{1}{\theta}\mathcal{H}(v \longmapsto C))$ if $\mathcal{H}(v \longmapsto C)$ is larger than zero or 0 otherwise. θ is a parameter measuring the degree of randomness in the selection of a community [51]. This step is repeated for each community S.

3. Aggregation phase. After the partition P is refined, a new aggregation of nodes is required to built a new graph G' such that communities become nodes in G', i.e., $V(G') = P$ and $E(G') = ||[(C, D)|(u, v) \in E(G), u \in C \in P, v \in D \in P]$.

4. Steps (1), (2) and (3) are repeated iteratively until no further improvements can be made.

[51] According to Traag et al. (2019), randomness in the selection of a community allows the partition space to be explored more broadly.

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