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Factionalism, competition, and efficiency in Russian banking

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Abstract

This work develops a new quantitative text analysis methodology to identify, quantify, and assess factional influence on the financial performance and the likelihood of survival of Russian banks. Factional media association is found to have a positive effect on bank financials and business survival, with factional ownerhsip having the reverse effect. Two factions, the *siloviki* and persons associated with the government and the Presidential Administraion, are found to have a significant relationship with the likelihood of business survival.

Contents

List of Figures

List of Tables

Glossary

siloviki	current or former representatives of the intelligence community and certain military units. 4–6, 12, 26, 27, 29–31
ASV	*Agenstvo po Strakhovaniyu Vkladov*, Deposit Insurance Agency. Legally independent from the Bank of Russia, responsible for payouts to depositors of banks that face financial misconduct investigations. 6, 9, 28
Bank of Russia	the Central Bank of Russia, also referred to as the CBR. Responsible for industry oversight and monetary policy. 6, 16, 28
FSB	*Federalnaya Sluzhba Bezopasnosti*, Federal Security Service. Successor to the KGB, responsible for intelligence and counterintelligence operations. 4, 5
GRU	*Generalnoye Razvedyvatelnoye Upravleniye*, the Main Intelligence Directorate. 4
State Duma	*Gosudarstvennaya Duma*, the lower house of the Russian Parliament. 3, 33
SVR	*Sluzhba Vneshney Razvedki*, the Foreign Intelligence Service. 4

Introduction

The field of Russian political economy seems to evolve in a clearly demarcated manner by the decade as, indeed, does the political economy of the country itself. From the 1990s, most studies were concerned with the apparent success or failure of privatisation efforts [Barberis *et al.*, 1996, Ellerman, 2003], the 1998 sovereign default crisis [Lokshin & Ravallion, 2000, Sutela, 2000], and the supposed economic interplay between newly elected officials, established business leaders, and organised crime groups [Cohen, 1995, Walberg *et al.*, 1998]. The noughties are, again, mostly characterised in terms of resetting the status quo, the seizure of business assets from some companies [Hanson, 2005], the consolidation of the oil industry and its eventual move under complete state control [Heinrich, 2008]. The prosperous 2000s are then replaced with the turbulent 2010s, where international sanctions resulting from some military adventures in Ukraine and Syria and the falling oil prices together bring about stagnation and a form of autarchy for the extracting sector and the food industry [Crozet & Hinz, 2020, Tuzova & Qayum, 2016]. Despite the economy as a whole growing more market-oriented, especially in sectors that are not considered essential to national security, there are still some bastions of state ownership such as the oil industry and, more notably, banking.

While some sectors, such as defence and oil and gas, are completely subservient to the state and, therefore, uncompetitive and inefficient, the banking sector remained relatively variegated from the boom of the late 1990s to early 2000s, up until the culling undertaken in the recent years by the Central Bank [Cordell, 2019], which begs the question: what personal associations influence banks' decision-making, success, and the odds of survival? Are those associations more or less important than a bank's competitiveness and efficiency? As shown in my previous work [no. 36058, 2019], there is strong evidence for the conjecture that the efficiency of credit allocation and the resulting levels competition and competitiveness are strongly influenced by the geographic position of the registered headquarters of a bank, with the most efficient and competitive banks being registered in the 'two capitals', Moscow and St Petersburg, and some old industrial areas, which gives some credence to the suggestion that the enterprises those banks serve might also play a role in how efficiently the latter are run. Another influence factor that is determined is ownership, with partially or fully state-owned banks being more cost-efficient and more income-efficient when compared to independent local banks or independent foreign-owned ones. In my work I suggest a further avenue to explore in studying competition and efficiency of banks: factionalism. It is a feasible assumption that most banks will have certain clientele that would depend on their factional associations as well as on their regional and ownership ties, and that certain bureaucrats may exert influence over banks that may result in differing financial and business outcomes.

Research questions: What factions exert influence on banks? Are competition and efficiency more or less important than factional association in determining success in the banking industry?

Hypotheses: We hypothesise that there is notable, if not outsized influence that certain factions exert on banks, and that efficiency and competitiveness are at least as important to business success as factional association.

Methodology: This paper develops a novel mixed-methods methodology for the assessment of factional influence, which combines the analysis of media mentions of individuals from particular factions in bank-related news with ownership documents and accounting reports.

Data: For this work, I compile a new data set of mentions of faction-associated individuals using natural language processing techniques, linking those mentions with particular banks and their financial performance and ownership data.

Chapter 1

Literature review & methodology

The only comparable study on factions in finance has been done by Victor Shih [Shih, 2007], who discovered that there is a relationship between the prevalence of generalist ot technocratic factions in China and inflation—the economy heats up during a generalist period and spending is curtailed under technocrats. Shih focuses on macroeconomics influences of factions in a country, whereas the focus of this paper is the microeconomic impact of factional association on individual banks. Other studies in the area rely primarily on text analysis, interviews, and and simple summary statistics [Hutchcroft, 1998, Boone, 2005].

1.1 Identifying factions

The paper will use mixed methods but will lean heavily on quantitative analysis to single out representative case studies for each influence group. In this paper, a faction is not directly defined as a party or grouping in parliament, as parliamentary factions in the State Duma are generally subservient to the government of the day (or decade) [Noble, 2015] and one's presence in parliament is the result of previous activity in regional administrations, security services, or business [Kynev, 2017]. There are, however, distinct groupings of elites within the government itself, which appear to be based on their career paths to date and their prior social and bureaucratic associations, and that dictate the three crucial variables determining their influence: the access to administrative, monetary, and political resources. In order to be identified as a distinct faction, a group has to have access to at least two of these resources. Judging on these criteria, the relationships banks have with the following groups will form the backbone of analysis. A simple breakdown of the criteria as applied to each faction is presented in Table 1.1 on page 4.

Table 1.1: Factions and their resources in Russia.

Faction	Faction resources		
	Administrative	Political	Monetary
Duma	— parliamentary investigations	— media pressure — personal networks	— budget approval — subsidy approval
Finance lobby	— connections with regulators	— lobbying activities	— investment — credit allocation
Intelligence	— curator network — power to access data — informants within organisations	— media pressure — raids/*maski-show* — *compromat*	— legal prosecution — account freezes
Law enforcement	— power to access data	— raids/*maski-show* — personal networks	— legal prosecution — account freezes
Officer	— bureaucratic connections — procurement decisions	— media pressure — personal networks	depends on other factional associations
Oligarchs	— rubberstamping regulators — self-policing	— media pressure — pocket politicians — personal networks	— ownership of businesses — bribery
President	— the power vertical — telephone justice	— media pressure — political persecution	— budgeting — budget approval — power over tax authorities
Regional	— (limited) bureaucratic oversight — land use permissions	— local media pressure	— limited discretion over regional subsidies
Resource lobby	see oligarchs above	see oligarchs above	see oligarchs above
Technocrats	— bureaucratic oversight — power to access data	— media pressure — personal networks	— budgeting — power to seek back taxes

First, the *siloviki*, or the current and former representatives of security services, such as the FSB and the Economic Crimes Agency under the Ministry of Interior are good candidates due to their deep involvement in almost all business expropriations in the past two decades. Every enterprise of any significance is assigned a curator from the FSB who is responsible for knowing the ins and outs of the business and seeing who its beneficiaries are [Georgiev, 2008, Ware, 2013]. To determine whether a bank is at any particular risk of falling foul of the *siloviki*, we must find reports of so-called 'masquerades', or *maski-show*—masked raids by the *siloviki* on banks' offices to seize business records or intimidate its owners, as may be the case with other players in the financial market like Bill Browder's Hermitage Fund [Browder, 2015] or other strategically important organisations such as those in the media sphere [Lipman & McFaul, 2001]. Such associations are easy to match within the biographical data collected on persons in the lobbyists data set, which also includes their temporal factional associations, simply boiling down to a keyword search on FSB, its predecessor KGB, the GRU and the SVR, for whether an individual holds or has ever held the rank of Lt Col. and above in either the Russian Army, the Red

Army, or the police force.

Such collective designation, however, risks including too many individuals in the faction and may be unable to distinguish between officers from the army, where access to the banks may be restricted fur to the nature of their work, and the FSB, whose associations with the industry may be stronger due to their direct involvement in fraud and corruption investigations, as well as in *maski-show* [Rochlitz, 2019]. For the same reason, there is a need to distinguish high-ranking officers from the army and the police force in the conventional definition of *siloviki* from ones who hold more sway over the process and who are much closer to the centre of power. Thus, we subdivide the *siloviki* into three groups: any high-ranking officers from the army or the police force, any operatives from the intelligence services, and, finally, ones reporting to the Ministry of the Interior, ie. the police force, or other law enforcement agencies such as the Federal Bailiff Service and the Federal Peniterntiary Service.

Second, the connection with the oligarchy should also be fairly obvious as they control vast financial resources [Guriev & Rachinsky, 2005] and would require a convenient means to channel those—a bank. Their names would usually be in the banks' charters or in news reports of dealings their companies have had with a bank—media reports from reliable sources will form the basis of our judgement here. As to the definition of oligarchic influence, the primary criteria for a person to be included in the list of oligarchs would be their involvement in big-stakes business, be it in the extracting industry or in the financial services; and their simultaneous former or current direct presence in the corridors of power, or similar presence through associates [Fortescue, 2006]. The nature of the relationship is immaterial for the purposes on this paper, as gathering such data would, firstly, preclude unbiased analysis of the influence the mere existence of such a relationship has on a bank's financial performance and survival; and secondly, impose prohibitive time costs due to the sheer volume of information already collected. Due to space constraints, therefore, we only analyse the mere presence of factional association and the direction of its effects, leaving the question of extent and nature to future research in the area.

Whether a person can be considered an oligarch is a wooly question: even the most oligarchic of men, such as Alisher Ousmanov [Tatdayev, 2018] and Oleg Deripaska [Gazeta.ru, 2009], are keen to distance themselves from the term. Others, on the other hand, may certainly qualify based on their fortune but would not make the cut based on their political clout, such as IT moguls Eugene Kaspersky [Forbes, 2020] and Pavel Durov, with the latter in self-imposed exile after having been forced to sell his stake in the Russian equivalent of Facebook, VK [Hille, 2014]. For these purposes then, an oligarch is anyone who rubs shoulders with the highest levels of Russian bureaucracy, occasionally being forced to do their bidding lest some irregularities are found in their business accounts. It is also anyone who participated in the privatisation programmes of the 1990s and, through their connections in the cash-strapped government, managed to score lucrative deals on formerly state-owned assets [Glazunov, 2013]. It is not, however, *any* person of considerable wealth, as the authors of a US Treasury report would like to present in their 'oligarch' list drawn up as a half-hearted response to CAATSA legislation [Mnuchin, 2018], which appears to have been almost entirely copied from the Russian Forbes 100 list and, in its iteration for the bureaucracy, from the Kremlin's website [Taylor, 2018]. Such lack of sophistication is not justified in this classification, so we rely on a tried and tested, albeit blunt, keyword search approach for the terms 'oligarch' and 'privatisation' throughout the biographies, trusting the professional opinion of government relations specialists from *Lobbying.ru*. Further, despite the fact that the vast majority of oligarchs would have made their fortunes during privatisation spree in the 1990s and mostly own assets in resource extracting industries, others were involved in the fledgling financial market and tried to set up banks or other financial institutions, which is a crucial distinction for this paper. Thus, by distinguishing between oligarchs who owe their fortunes to oil, gas, and minerals, and ones who were attempting to provide financial services, we are able to measure more precisely their respective effects on financial performance and survival odds. Such an approach also allows us to capture not only the resource/banking oligarchs themselves, but also any officials who may have had business or other dealings with them.

Third, we shall look at any evidence of influence by the technocrats in the government, or any former business and regulator-regulatee relationships the officials have had with a bank. Such relationships may constitute anything from innocent coincidental mentions of names due to participation in an industry conference to reports of licence revocations by the Bank of Russia and the subsequent payouts by the ASV, or even raids by the *siloviki*. Again, the direction of this relationship is not pertinent to the part of the paper in which we quantify the influence of factional association on the bank competitiveness and efficiency, but we touch upon the details of such a relationship in the qualitative analysis section of this work. The basis for taking this group as a distinct faction is their control over administrative approvals for certain deals banks may have with their clients, and the resulting problem of delegation where a principal may be unaware of how much power an agent actually wields. In this sense, the administrative approvals for large financing deals between banks and construction companies or other players in the lucrative government procurement market are prone to influence by ministers and their deputies, who may not want to yield their turf and demand kickbacks for administrative approvals. Another related subset of technocratic power may be the Presidential Administration, representatives from which may wield more political power and therefore be able to influence technocrats in the government. They deserve a separate category as, even though they have to be mildly technocratic, their main objective is to ensure that presidential decrees and promises and carried out by the government.

Fourth, with regionalism proven to influence efficiency and competitiveness of banks, we shall classify banks based on whether they are registered in a central location or in one of the regions, which increases the likelihood that they will be prone to influence by regional cliques—be they connected to business, the officialdom, or organised crime [Libman & Kozlov, 2013]. On the side of biographical data we perform keyword searches for 'governor', 'mayor', variations of 'regional administration'. The likelihood that such searches result in reliable matches is high, as the biographical data contain mostly factual information in the format of a CV, so accidental associations are improbable. Whether such factional associations are maintained is an open question and one that future work on the matter will have to answer—the rough keyword search approach is, again, dictated by computational and time constraints, as it is not feasible to process manually more than 4,000 biographies at this stage. Therefore, regional associations need to be taken with a grain of salt and are to be confirmed or refuted using qualitative analysis further on in this project.

Obviously, one bank may fall under the purview of more than one faction, or none at all, just as one individual may belong to various factions at the same time, may formerly have had associations with a faction that may still be in play. All such permutations should be captured within the aggregate data on media mentions in a particular context, ie. if an individual's name is mentioned within a certain time period during which they identifiably belonged to one faction, we can trust the database to associate such cases appropriately with their biographical data based on those dates. Conversely, if no concrete association may be inferred, the cumulative number of matches may be indicative of the prevalence of one faction over another in case one bank or one individual is associated with more than one faction.

1.2 Identifying influence factors

Having identified factions whose influence over banks may result in changed efficiency and competitiveness, we should now turn to the methods for inferring such influence based on the available data. I propose that such influence may be overt or covert, and weak or strong. An overview of potential types of factional association is presented in Table 1.2 on page 8.

Table 1.2: Typology of factional influence on banks.

Strength of influence	Type of influence	
	Overt	Covert
Weak	— media mentions	— indirect signalling — network pressure
Strong	— licence revocations — *maski-show*	— ownership ties — threat of licence revocation

1.2.1 Media mentions

Media mentions of a particular faction-associated individual in a news item associated with a particular bank are easily quantifiable based on the available data. By definition, such factional influence is overt, as it is not carefully kept out of the public eye or, at least, away from the the professional audience. Their factional influence on competitiveness or efficiency is not determinable at this stage, as we can only quantify the number of mentions per bank per faction per individual and leave the directionality to future research. This influence is weak due to the transient nature of a mention in an article and due to the varying degrees of journalistic integrity in Russia. However, such mentions have their strength in volume, so if a certain individual is repeatedly mentioned within articles about the same bank, it is a reliable indicator of factional influence.

1.2.2 Administrative pressure

Administrative pressure can be exerted in a variety of ways, most of which have mild to strong influence over banks. First, strong and overt influence like licence revocations and maski-show would represent the final resort for factions and would not necessarily explain what factions are responsible for such outcomes. For example, if the owner of a bank is a former intelligence officer and is now considered an oligarch, we have no way of knowing whether the revocation is the result of network pressure or of actual financial misconduct by the bank, and whether such revocation is followed by a lawsuit from the ASV attempting to repossess diverted funds might indicate stronger or weaker administrative resources for the faction controlling the bank. Whether licence revocation or a lower competitiveness/efficiency score is the result of milder pressure from other factions is unknowable. All this demonstrates is the improbability of attributing a single action to one faction for every single bank in the data set, leaving us to rely on the binary revocation variable to ascertain which faction may have had a larger effect on an average bank, not a particular one—for this, we estimate a logistic regression model with revocation/dissolution as the dependent variable.

1.2.3 Ownership

Arguably the strongest of all associations is the one owners have with their business as they have voting rights and retain final decision-making power even if they choose not to participate in the day-to-day management of the bank.

1.3 Quantifying factional influence

1.3.1 Index of media mentions

The strength of factional association a bank has in the media, or the Faction Media Index (FMI), can formally be written as follows:

$$FMI_{b,p,f,t} = \sum_{b,p,f,t=1}^{b,p,f,t} \frac{m_{p,t,f}}{\sum_{b,p=1}^{b,p} m_{p,b}}, \tag{1.1}$$

where
b is the bank, represented by its unique registration number, or *regn*;
p is a particular faction-associated person;
f is the faction under consideration;
t is the time period under consideration; and
m is the number of mentions of that person in a news article associated with a particular bank.

In plain language, the strength of factional association for a bank in the media ($FMI_{b,f,t}$) is determined by the number of mentions of faction-associated individuals in a certain period of time divided by the total number of mentions for all names mentioned in articles mentioning that bank.

1.3.2 Index of mentions in ownership statements

The strength of factional association a bank has in the media, or the Factional Ownership Index (FOI), can formally be written as follows:

$$FOI_{b,p,f,t} = \sum_{b,p,f,t=1}^{b,p,f,t} \frac{o_{p,t,f}}{\sum_{b,p=1}^{b,p} o_{p,b}}, \tag{1.2}$$

where
b is the bank, represented by its unique registration number, or *regn*;
p is a particular faction-associated person;
f is the faction under consideration;
t is the time period under consideration; and
o is the number of mentions of that person in the ownership report associated with a particular bank.

Thus, the strength of factional ownership association for a bank ($FOI_{b,f,t}$) is determined by the number of mentions of faction-associated individuals in a certain period of time divided by the total number of mentions for all names mentioned in ownership reports for that bank.

1.4 Quantifying competition and efficiency

1.4.1 Lerner index

To appraise competitiveness and pricing efficiency, we borrow the Lerner indices computed in my previous work for each of the banks in 2013. The index measures an individual firm's markup on its output by subtracting marginal costs from the prices of its outputs. The formal representation of the Lerner index is as follows:

$$Lerner_{b,t} = \frac{Price - MC}{Price}, \tag{1.3}$$

From this, we can interpret a bank which has a Lerner index that approaches or exceeds 1 to have monopolistic or oligopolistic power in the industry, and a negative value would indicate a bank that cannot purposely mark up its services because of fierce competition or competitive pricing [Lerner, 1934]. This paper obtains the Lerner index based on the methodology set out in [Koetter *et al.*, 2012], accounting for market efficiency as well as market structure. As the calculations involved are computationally intensive, the Lerner index is only available for the year 2013. Any studies on the intertemporal distribution of Lerner indices would require more computational power and would detract from the main topic of investigation, for which reason it is outside the scope of this paper. Other works employing the Lerner index in the banking industry suggest there are possible links between competitiveness and efficiency [Fungáčová *et al.*, 2012], which allows us to use the index with a dual purpose: to assess the competitiveness of a bank as well as its efficiency.

1.4.2 Data Envelopment Analysis

Data Envelopment Analysis (DEA) is a linear programming optimisation technique for measuring the most efficient way of producing output whilst minimising costs. As computed in my previous work on regionalism, the cost function takes the following form, as shown in Chen et al. [Chen *et al.*, 2005]:

$$C = C\left(p, y, z, v, \varepsilon\right), \tag{1.4}$$

in which
p represents input prices (prices of capital, labour, and physical capital),
y is a vector of outputs (loans and interest income),
z is a vector of fixed bank parameters (total equity, total assets), and
ε is the error term.

The rest of the model relies on the assumption of variable, not constant, returns to scale as Russia's banking sector is not fully developed. Chen et al. [Chen *et al.*, 2005] formulate the optimisation problem in the following way:

$$\min_{\theta,\lambda}, \; when \; -y_i + Y \geq 0, \theta x_i - X\lambda \geq 0, \lambda \geq 0, \tag{1.5}$$

where
θ is a scalar,
λ is an $N * 1$ vector of constants,
Y represents all input and output data for N firms,
x_i are the individual inputs and
y_i the outputs for the i^{th} firm [Coelli *et al.*, 2005].
θ represents our requisite efficiency score and is linked to a decision-making unit (DMU), which in our case is the registration number *regn* for each of the banks in the sample.

A previous work on efficiency in Russian banking used stochastic frontier analysis and found that foreign-owned banks the least efficient [Mamonov & Vernikov, 2017], whereas in my study on regionalism I find that the most efficient banks are registered in the Central Federal District, specifically, Moscow [no. 36058, 2019]. Again, due to computational intensity only the DEA scores for 2013 are considered in this paper, which is a reasonable choice for two reasons: first because the banking system had not yet experienced the exogenous geopolitical shocks of 2014, and second—because by then the industry cleansing campaign had not yet devoured as many banks, so we would be capturing its 'natural' state.

1.4.3 Bank Efficiency Ratio

The bank efficiency ratio is a simple accounting indicator which can be computed for all years through which we possess the data, and is formally written as follows [Furst *et al.*, 2002], where a higher ratio indicates lower efficiency:

$$BER = \frac{Noninterest\ Expenses}{Total\ Revenue}. \tag{1.6}$$

1.5 Qualifying factional influence

As has been discussed at length in Section 1.2, the nature of factional influence cannot be extracted from pure numerical values of indices and, as such, we cannot draw inferences on their effect on the efficiency and competitiveness of a particular bank. To be able to put numbers in context, we shall pick out a few banks with variable factional associations and business outcomes to illustrate the influence of each faction. Such case studies may potentially include the actions of factions resulting in favourable treatment of a certain customer or, conversely, in acting in a manner that threatens the credit institution's business credibility to pressure a credit institution into compliance with legal or extralegal demands, or a mixture thereof. Individual financial circumstances leading to factional influence should also be considered, as it may be the case that, for example, raids by *siloviki* are justified due to illegal financing activities or outright fraud. For each case we shall look at all possible actors and determine the extent of their influence on the bank's competitive standing.

Chapter 2

Data

This chapter reports on the data collection and data base linking process, some necessary transformations and the creation of new measurement techniques. This section provides summary statistics on the data collected and highlights the data points necessary for our analysis.

2.1 Data collection

All data sources in this paper are public but, to the best knowledge of the author, have never been combined in this way. First, we create a biographical database of Russian elites spanning three decades and including their factional associations based on matches on keyword searches from their respective biographies. Second, their lobbying activities are recorded and coded. Third, all articles from a trusted industry website are scraped and associated with particular banks, the names mentioned in those articles are extracted and linked to banks. Fourth, we supplement the data on lobbying with official anti-corruption declarations to check the data against official sources. Fifth, the accounting statements from 2012 to 2018 are collected and aggregated to include the indicators pertinent to the discussion of competitiveness and efficiency. Finally, we process all ownership and influence statements issued by the Bank of Russia, extracting the names of individuals mentioned there and linking the data sets based on the names to faction-associated individuals. Below is a detailed account of this data escapade.

2.1.1 Web scraping

Since we rely mostly on media reports for analysis, the Processing ephemeral literature such as industry news requires a lot of processing power and is prone to error and misattribution due to the sheer volume of information that needs to be processed. Topic analysis is therefore a useful but time-consuming technique which requires manual classification of thousands of articles. In order to automate this process and arrive at labels in an error-free way, we can employ an approach which which requires a little more technical skill but which can yield a quality data set in a fraction of the time the process would otherwise consume: web scraping. It is a way of extracting structured information from the web with little human involvement apart from the initial setup of the web crawler. Web scraping is rarely used in academia, apart from certain fields that rely on open data, such as bioinformatics [Glez-Peña *et al.*, 2014] and data science [Hardin *et al.*, 2015], but has the potential to help unearth insights in hitherto unstructured biographical and news data. The data set developed for this paper is a stepping stone to further data-driven approaches to analysing factions in modern Russian bureaucracy and business, potentially paving the way for papers utilising network analysis techniques as demonstrated in [Guleva *et al.*, 2015] to illustrate the complex interplay between factions and address the shortcomings of the current data by taking into account the fact that one individual and one bank may belong to multiple factions.

2.1.1.1 Justification for web scraping

There is an argument to be made against web scraping on the grounds that it may be equated to accessing privately held information without prior permission from its owners, however, this reasoning only stands in case one is scraping personal data that are somehow proprietary and protected. In the case of using publicly available data such as news articles, this does not apply. As Judge John Bates of the District of Columbia District Court wrote in his decision on the matter brought forward by cybersecurity researchers [Sandvig, 2018, p. 32],

> The use of bots or sock puppets is a more context-specific activity, but it is not covered in this case. Employing a bot to crawl a website or apply for jobs may run afoul of a website's [Terms of Service], but it does not constitute an access violation when the human who creates the bot is otherwise allowed to read and interact with that site.

Further to this, in an injunction on the matter the US Court of Appeal for the Ninth Circuit decided that scraping publicly visible and accessible data does not violate the Computer Fraud and Abuse Act (CFAA) pending further appeals [Chen *et al.*, 2019]. The case is likely to attract the attention US lawmakers who might legislate on the practice. To the best knowledge of the author, there have not been any similar cases brought forward in the European Union or Russia. Using this legal reasoning, we can justify the need to obtain the requisite databases by means of web scraping.

Further, from the ethical perspective a list of seven questions is provided in [Krotov & Silva, 2018, p. 4], to all of which we can answer 'no': the Terms of Service on the websites used do not explicitly prohibit web scraping; the data on the website come from open sources and are therefore not subject to copyright; the project does not involve illegal use of data; the scraping process is distributed and auto-throttled and can therefore not damage server infrastructure; no personal information is scraped apart from that which is already available from other open sources (ie., the mentions of names in the articles); and the project does not diminish the value of the services the websites provide.

2.1.1.2 Source selection

Since the aim of the paper is to associate individual banks with factions, we need to consider multiple data sources that would provide a complete list of banks and the people involved in running them or otherwise associated with them; and a complete list of factional associations of the Russian elites. The task, therefore, is twofold: to obtain a list of individuals—prominent politicians, businesspeople, and industry lobbyinsts—with their respective biographies, matching them with the requisite factions; and to join the names of individuals extracted from articles with the data on faction-associated individuals.

Lobbying.ru *Lobbying.ru* is a professional government relations website which provides information on the involvement of eminent public persons in the legislative and bureaucratic processes, and also includes structured data on their career timelines. The data for a randomly chosen sub-sample of 50 people matches up with information from cross-referenced sources such as newspaper articles and official biographies.

The architecture of the scraper included the following elements: the URLs for lists of people in individual lobbies, the corresponding links to the pages of individual biographies, individuals' names, short biographical descriptions and their full biographies, including education and careers. The links to other individuals were preserved to simplify the process of joining the data sets. In total, the data set contains biographical and career data on 4,724 individuals [Lobbying.ru, 2020]. The source code for this scraper is available on page 32 in the appendix.

Banki.ru *Banki.ru* is a leading industry website for the banking sector in Russia which collates information from banks themselves in the form of press-releases, news articles about banks copied from other reliable sources, financial data from the Bank of Russia, and customer reviews.

The architecture of the web crawl included the following elements: article type and date, its URL, the URL tags for individual banks mentioned in the article, and the individual information pages for banks with their addresses, bank registration numbers, a brief history of the bank, and a short description of its main business. As with the scraper mentioned above, a separate Github repository containing the source code is available online. In total, we obtain 21,605 unique articles on 2,696 unique banks.

2.1.2 Anti-corruption declarations

We utilise a database collated and published by Transparency International—Russia which comprises personal information on individuals holding public office or civil service positions, their political associations and data on income, the disclosure of which is mandated by Russian laws on open government data [Russia, 2006], which states that it is not necessary to obtain individual consent when working with data published as a result of data disclosure mandated by federal law. This information was used to cross-reference the validity of biographical and professional data from *Lobbying.ru*.

2.1.3 Accounting statements

Full accounting statements filed by each bank with the Bank of Russia for years 2012 to 2018 are used to obtain financial performance information aggregates by means of SQL queries. We use the methodology published by *Banki.ru* for finding the accounting codes to obtain the requisite aggregate values for each bank and time period.

2.1.4 Bank of Russia ownership/influence statements

The Bank of Russia provides 3,015 ownership and influence statements for all banks from 2016 to 2020 in *.pdf* format on its website [Central Bank of Russia, 2020], which we download using the scraper on page 34 in the appendix and process using the same technique used previously for news articles: named entity recognition for each statement and entity linking with faction-associated names. The programme is presented in the appendix on page 34.

2.2 Data engineering

Banki article URLs are linked with banks based on URL tags which, in turn, contain references to bank information pages on Banki.ru whence we can obtain their unique registration numbers issued by the Bank of Russia. This allows us to link banks to articles and accounting data without fearing misattribution, as may be the case with surnames.

For names, the resulting matches are normalised using the natural processing library Natasha in the Python programming language, eg. a declined form of the masculine surname in the dative case *Ivanovu* would be changed to a masculine singular nominative case *Ivanov* as all names in the lobbying database are in this initial form.

2.3 Data processing

2.3.1 Named entity recognition

Preserving the metadata such as bank registration numbers and dates for each article and ownership statement, we build a custom named entity recognition model using the natural language processing library Natasha [Veselov, 2016] in the Python programming environment, receiving 8,431 unique names grouped by spelling to capture the various inflections names have in different grammatical cases in Russian. The resulting code for this programme can be found on page 34 in the appendix. Table 2 on page 32 presents statistics on the number of names identified in all articles broken down by factional association and news source as attributed by *Banki.ru*.

2.3.2 Joining data sets

All surnames located in the articles and ownership statements are split off from given names and patronymics matched to the ones in the biographical database. We reduce the likelihood of false matches by manually sifting through matches containing common Russian surnames and contextually disambiguating them. 2,540 names from the articles match those from the biographical database.

Chapter 3

Results

3.1 Factions in the media landscape

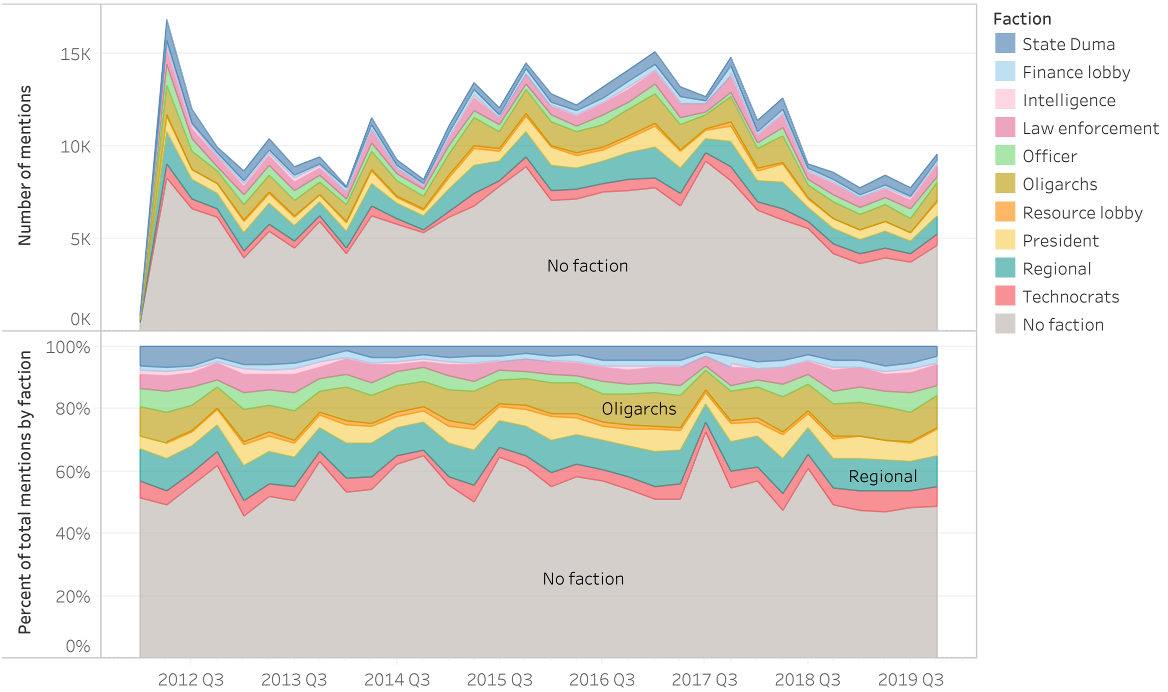

Figure 3.1: Strength of Russian banks' factional associations from media reports on *Banki.ru* 2012-2019.

As hypothesised, factions-associated individuals do appear to take up an outsized proportion of name mentions in bank news, with Figure 3.1 on page 18 indication that, in 2012-2013, such associations accounted for at least 40% of all mentions and, in some periods, rose up to 50%. We can therefore safely reject the null hypothesis of no association and further pursue out inquiry, attempting to link factional association with competitiveness and efficiency and understand in the strength of factional association has any effect on the fate of the bank: whether it is allowed to continue operations, told to wind down and dissolve, or forced to cease operations entirely as a result of licence revocation.

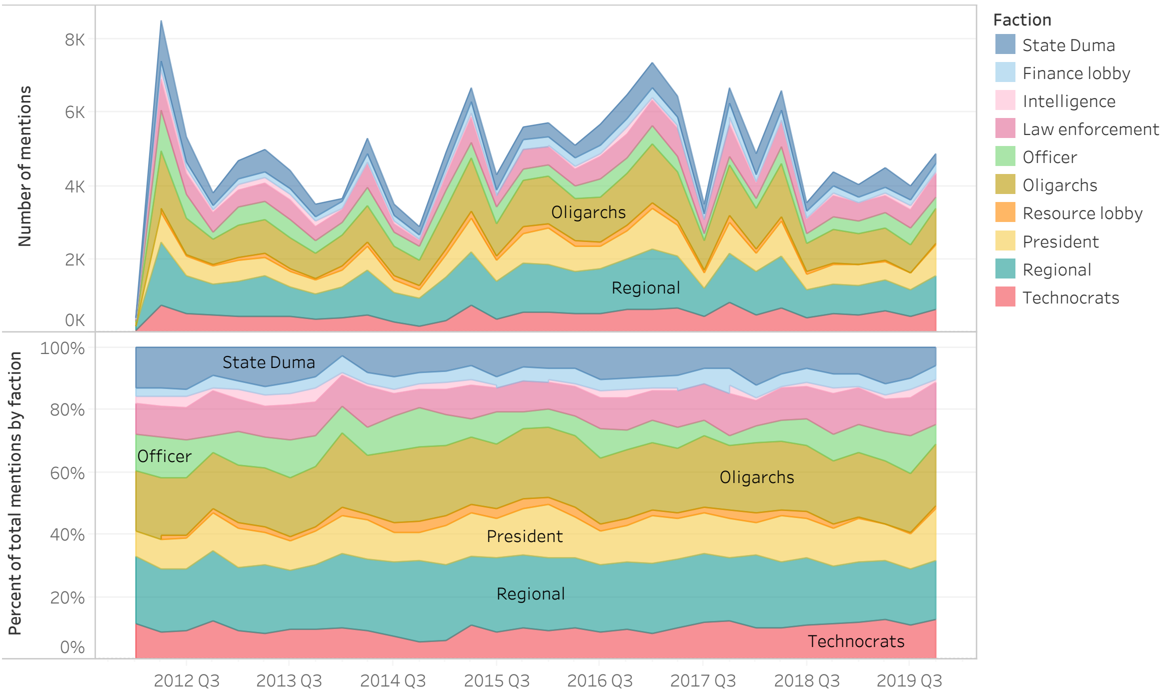

Figure 3.2: Strength of Russian banks' factional associations from media reports on *Banki.ru*, 2012-2019, excluding mentions with no faction attributed.

From Figure 3.2 on page 19 we can observe that state-associated factions, including technocrats, individuals associated with the Presidential Administration, regional administrations, law enforcement and intelligence agencies, contribute to at least three quarters of all mentions, with the oligarchy taking up the rest. To call oligarchs not state-associated would be disingenuous, but in this typology the oligarchy is legally distinct from the state, which is why it is worth trying to decouple their influence from that of state-associated factions. It is also worth noting that the resource lobby as a subset of the oligarchy does not seem to be represented widely enough to be considered a separate faction, unless it is responsible for some significant developments in banks serving the extracting industry. Intelligence agencies, predictably, generate the fewest mentions in the media but should still be considered a faction in its own right due the strength of their influence on banks in terms of investigations, *maski-show* and covert pressure. Such pressure is not easily quantifiable and will be considered in the qualitative assessment section of the work.

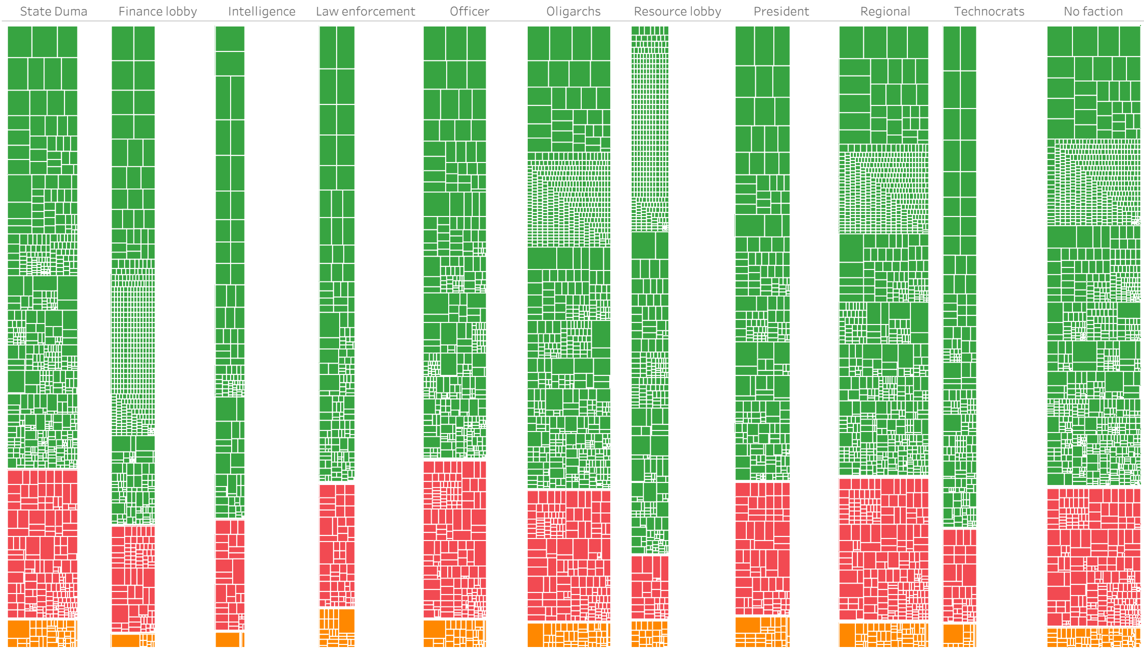

Figure 3.3: Faction Media Index (FMI) for Russian banks, 2012-2019, excluding Sberbank.

Legend on licence status: green—active, amber—dissolved, red—revoked.
Each rectangle represents an individual *Banki.ru* news item, its area corresponds to the news item's relative FMI.

Figure 3.3 on page 20 presents a granular depiction of each news item according to the size of its contribution to a certain bank's Faction Media Index (FMI). Mention of the largest bank in Russia, Sberbank (*regn.* 1481) are excluded as it has strong associations with all factions and therefore produces more than half the area for each faction, precluding further analysis. Broken down by licence status as of the time of writing, this infographic shows us a relatively even distribution of active and non-active banks across all factions: around 25% of the FMI is made up of mentions for credit institutions that ended up with their banking licence revoked. This indicates a not insignificant correlation of factional influence and business status, further lending credence to the suggestion that factional association may be one of the factors determining business success. As explained in Chapter 1 on page 3, we cannot infer any directionality and causality from this correlation until we consider the timeline of events and the interplay between factional and non-factional influences.

Table 3.1 on page 21 reports on OLS regression with robust standard errors of the influence of factional media association on profit. The model explains from 93 to 96.2% of variance depending on specification and the number of additional fixed effects variables. From it we can observe that FMI is positively correlated with profit

Table 3.1: Influence of factional media association on profit

	(1) Profit	(2) Profit	(3) Profit	(4) Profit	(5) Profit	(6) Profit
FMI	1456316719***	1318677779***	1275086336***	137375991*	132753442*	133274267*
	(100.54)	(69.62)	(62.74)	(2.23)	(2.20)	(2.21)
$\log(TA)$		699503***	1344760***	960616***	1497865***	1572215***
		(10.41)	(9.76)	(8.36)	(9.76)	(9.98)
$\log(EQ)$			-862588***	-318225*	-854057***	-935417***
			(-5.34)	(-2.34)	(-5.06)	(-5.39)
$\log(Lerner)$				837***	799***	794***
				(19.23)	(18.41)	(18.29)
$\log(\frac{EQ}{TA})$					1287059***	1355592***
					(5.17)	(5.41)
DEA score						-9211*
						(-2.00)
Constant	259173*	-10566730***	-8726015***	-10014464***	-12854438***	-12973437***
	(2.12)	(-10.10)	(-8.05)	(-11.22)	(-12.41)	(-12.53)
R^2	0.930	0.938	0.941	0.960	0.961	0.962
Adjusted R^2	0.929	0.938	0.940	0.960	0.961	0.961
Observations	768	768	768	768	768	768

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

and that a hypothetical fully-faction-associated bank, ie. one for which all name mentions are about faction-associated individuals, would enjoy at least RUB 1.2bn in extra profits. The table does not provide a breakdown by faction as specific FMI figures as independent variables did not yield statistically significant results. As extra explanatory variables we include log of total assets as a proxy for the level of market share, the logarithm of equity as an indication of the level of funding, the log of the ratio of equity by total assets as a measure of risk exposure. Finally, more pertinent to our analysis, we include the DEA score θ which explains allocative efficiency and the Lerner index, which indicates the competitive markup on a bank's products—the higher it is, the more a bank can afford to charge for the same service, and the more monopoly-like rents it can enjoy.

The extent of such an effect of factional media association on profit may at least partly be explained by the bigger state-owned banks like Sberbank and VTB-24, as they are almost equally associated with each of the faction under investigation and are, respectively, first and second in the ranking of banks on assets. The DEA appears to be negatively associated with profits, which indicated an inverse relationship of allocative efficiency with profits, albeit at a lower confidence level of 5%. Two variables of interest—FMI and the Lerner index—are positively correlated with profit and

Table 3.2: Influence of factional media association on total assets

	(1) log(TA)	(2) log(TA)	(3) log(TA)	(4) log(TA)	(5) log(TA)	(6) log(TA)
FMI	196.7667***	196.7346***	196.7671***	196.7696***	194.0500***	198.3525***
	(26.97)	(26.97)	(27.13)	(27.15)	(27.47)	(31.09)
Lerner		0.0000	0.0000***	0.0000***	0.0000**	0.0000**
		(1.44)	(3.41)	(3.38)	(2.94)	(3.23)
MC			0.0912**	0.0900**	0.0775**	0.0788**
			(3.11)	(3.07)	(2.71)	(3.06)
DEA score				0.0046	0.0051	0.0037
				(1.53)	(1.74)	(1.40)
Revoked?					-0.8041***	-0.7242***
					(-6.61)	(-6.59)
log(EQ/TA)						-1.7321***
						(-13.25)
Constant	15.4766***	15.4743***	15.4639***	15.4556***	15.9352***	18.3784***
	(251.27)	(250.95)	(251.83)	(250.94)	(169.31)	(90.53)
R^2	0.487	0.489	0.495	0.497	0.524	0.613
Adjusted R^2	0.486	0.487	0.493	0.494	0.521	0.610
Observations	768	767	767	767	767	767

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

do not appear to deviate significantly in relation to each other when other variables are dropped or added. This can be interpreted as follows: banks which appear to be more strongly faction-associated in the media enjoy higher profits, controlling for their efficiency and competitiveness, levels of risk and market share. In line with our hypotheses, factional media influence is a significant positive predictor of profits at the 0.01% confidence level, ie. we are 99.9% confident in the direction and extent of such a relationship.

Table 3.2 on page 22 presents the OLS estimates of FMI on the log of total assets, largely confirming the results obtained in the previous model with the absolute value of profit, showing a positive association between the two variables that is significant at the 0.01% confidence level, controlling for their competitiveness in the, efficiency, an estimate of its marginal cost, risk level, and whether a bank eventually faced either the revocation of its banking licence or dissolution. The major difference with the previous model is the minuscule positive coefficient for the Lerner index and a small positive association with bank efficiency as measured by the DEA efficiency score. The regression coefficient for FMI indicates that for a fully-faction-associated bank would have, on average throughout the models, a level of total assets at least 195 times higher than that of a hypothetical bank with no factional media association whatsoever, which again confirms our hypothesis of factional association playing a part in determining the financial indicators of a bank.

Table 3.3: Influence of factional media association on the odds of licence revocation.

	(1) Revoked?	(2) Revoked?	(3) Revoked?	(4) Revoked?	(5) Revoked?
FMI	-330.3878*	-384.9008*	-384.9311*	-385.0139*	-363.6874*
	(-2.53)	(-2.50)	(-2.50)	(-2.50)	(-2.40)
$\log(\frac{EQ}{TA})$		0.2686	0.2740	0.2733	0.2496
		(1.45)	(1.47)	(1.47)	(1.26)
DEA score			0.0040	0.0040	0.0042
			(0.60)	(0.60)	(0.65)
Bank Efficiency Ratio				0.0864	0.0477
				(0.11)	(0.06)
MC				-0.0003	1.6140
				(-0.02)	(0.81)
log(Lerner)					4.1797
					(0.84)
Constant	0.5387***	0.0588	0.0450	-0.0296	-4.1342
	(7.42)	(0.21)	(0.16)	(-0.04)	(-0.83)
Pseudo R^2	0.013	0.015	0.015	0.015	0.020
Observations	874	768	768	768	768

logit values presented as coefficients, t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.3 on page 23 expounds on the relationship between the likelihood of having to terminate business due to licence revocation or dissolution, and factional and financial variables. By means of logistic regression we arrive at a negative relationship between the likelihood of business termination and factional media association, which means that the more faction-associated individuals appear in articles about the bank, the less its likelihood of having to cease operating. None of the other variables, such as DEA and accounting indicators of efficiency, risk levels, or competitiveness appear to be statistically significant predictors, although there are some variables that are borderline insignificant close to the 10% level.

In brief, the hypothesis that factional media association affects a bank's financial standing and the odds of survival is confirmed, with financial institutions likely to have higher relative share of total assets and profit with higher factional media association, and be less likely to have their licence revoked as compared to ones with little to no factional association. Having considered factional media association—covert weak influence—and found it to be a significant factor in determining some vital variables for a bank, we now turn to covert and strong influence—ownership.

3.2 Factional ownership

Despite the public nature of ownership information, it is not mentioned in the media as widely or as often as other faction-associated individuals affecting the day-to-day business of running a bank. However, in this section we do find significant effects of factional ownership on the financials and on the odds of survival.

Table 3.4: Influence of factional ownership on profitability

	(1) $\log(\frac{Profit}{TA})$	(2) $\log(\frac{Profit}{TA})$	(3) $\log(\frac{Profit}{TA})$	(4) $\log(\frac{Profit}{TA})$	(5) $\log(\frac{Profit}{TA})$
FOI	-189.2736**	-197.3867**	-209.3738***	-208.4427***	-184.6004***
	(-2.99)	(-3.21)	(-4.23)	(-4.21)	(-4.61)
Bank Efficiency Ratio		2.2738***	0.7882**	0.7725**	-0.1835
		(6.57)	(2.73)	(2.67)	(-0.77)
$\log(TA)$			0.2379***	0.2401***	0.0625***
			(19.44)	(19.41)	(4.58)
Revoked?				0.0694	-0.0042
				(1.20)	(-0.09)
$\log(Lerner)$					0.0002***
					(19.19)
Constant	15.3427***	13.3655***	10.9724***	10.9159***	14.5111***
	(410.73)	(44.10)	(40.15)	(39.37)	(49.68)
R^2	0.013	0.070	0.398	0.400	0.608
Adjusted R^2	0.011	0.068	0.396	0.396	0.605
Observations	698	698	698	698	698

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In a surprising finding, we observe from table 3.4 on page 24 that factional ownership is inversely related to a bank's profitability as measured by the logarithm of profit scaled by total assets. Thus, a hypothetical bank which is wholly owned by faction-associated individuals would have profitability that is at least 184 time lower that that of a hypothetical bank with no factional ownership. Other bank fixed effects such as competitiveness and the log of total assets are significant positive predictors of profitability, while the Bank Efficiency Ratio does not seem to be a consistent determiner for it, as does the business termination dummy variable. The full model explains 60.5% of the variance in profitability. Factional ownership did not yield any statistically significant effects on the raw profit figure, and those regressions are therefore omitted from the paper.

Table 3.5: Influence of factional ownership on total assets

	(1) $\log(TA)$	(2) $\log(TA)$	(3) $\log(TA)$	(4) $\log(TA)$	(5) $\log(TA)$
FOI	72.6757	367.2790**	343.0297**	343.0866**	343.0637**
	(0.46)	(2.92)	(2.76)	(2.76)	(2.76)
$\log(\frac{Profit}{TA})$		1.5565***	1.4826***	1.4816***	1.4817***
		(20.81)	(19.44)	(19.45)	(19.44)
Bank Efficiency Ratio			2.8741***	2.8988***	2.8965***
			(4.01)	(4.05)	(4.03)
DEA score				0.0052	0.0052
				(1.54)	(1.54)
$\log(Lerner)$					-0.0000
					(-0.05)
Constant	15.4907***	-8.3902***	-9.7550***	-9.7721***	-9.7706***
	(165.10)	(-7.30)	(-8.22)	(-8.24)	(-8.23)
R^2	0.000	0.384	0.398	0.400	0.400
Adjusted R^2	-0.001	0.382	0.396	0.397	0.396
Observations	698	698	698	698	698

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.5 on page 25 indicates a positive relationship between FOI and total assets, controlling for risk exposure and bank efficiency. The DEA score and the Lerner index do not contribute to any major increases in explanatory power and do not have a statistically significant relationship with the independent variable and can therefore be omitted from the model, leaving us with only the FOI, profits scaled by total assets, and the Bank Efficiency Ratio, which together explain 39.6% of the variance in total assets. As expected, profitability was positively correlated with total assets, as was efficiency.

Table 3.3 on page 23 represents a breakdown of the influence factional ownership has on the likelihood of having to terminate operations. Of all the variables under examination, only the regional faction, the oligarchy and their subset—the resource lobby, have a statistically significant relationship with the dependent variable. FOI for banks with no factional association, however, appears to be This model provides inconsistent results and must therefore be improved on by considering other variables.

Table 3.6: Influence of factional ownership on business survival

	(1) Revoked?	(2) Revoked?	(3) Revoked?	(4) Revoked?	(5) Revoked?	(6) Revoked?
FOI	9.6684	357.7043	355.6619*	404.0170*	403.3918*	403.9675*
	(0.52)	(1.88)	(2.11)	(2.32)	(2.32)	(2.32)
siloviki		-938.9535	-1454.3871*	-1600.3408**	-1599.0352**	-1600.4876**
		(-1.86)	(-2.57)	(-2.73)	(-2.73)	(-2.73)
Government & President			1691.7622**	1725.3772**	1727.1214**	1727.3925**
			(2.73)	(2.70)	(2.70)	(2.70)
Overdue loans				-0.0000**	-0.0000**	-0.0000**
				(-2.74)	(-2.75)	(-2.74)
DEA efficiency					0.0040	0.0040
					(0.61)	(0.61)
log(*Lerner*)						0.0001
						(0.08)
Constant	0.2983***	0.2900***	0.3205***	0.4012***	0.3948***	0.3921***
	(3.89)	(3.77)	(4.12)	(4.94)	(4.84)	(4.80)
Pseudo R^2	0.000	0.005	0.014	0.034	0.034	0.036
Observations	714	714	714	714	714	714

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Chapter 1 on page 3 we considered factions to be split along the lines of actual control, but in this granularity the cumulative effects of some larger faction may have been lost. To account for those effects, we add up the FOI figures for intelligence, officer affiliation, and law enforcement to receive the cumulative FOI for the broader definition of *siloviki*. The FOI data points for the Presidential Administration are also summed with the technocratic faction to obtain a cumulative measure named Government & President. From these, we obtain a new granular model for the odds of business termination, which is presented in Table 3.6 on page 26. Cumulative FOI still remains a significant positive determiner of eventual business termination, while the ownership association with *siloviki* has a negative effect on this dependent variable. Ownership association with the government and the presidential administration, on the other hand, has a positive effects on the odds of business survival, ie. a negative effect on the odds of licence revocation. Another factors that significantly improves model fit is the amount of bad loans, which may have varying interpretations which will be explained further in the discussion of the results.

So far we have quantified and determined the direction of influence factional media association and factional ownership have on profitability and sustainability of the business, highlighting the their cumulative effects on the variables of interest. Granular models employing factional FOI have shown that we are left with only two factions of interest: the combined presidential and governmental faction, and the one combining ownership influence from the *siloviki* under the umbrella definition of the term. We now turn to two case studies which are broadly representative of some of the features of the models discussed here.

3.3 Bank-faction profiles

There are a myriad examples to choose from in terms of faction-associated banks, but to maintain a brief and representative sample and to avoid describing repetitive scenarios, we will keep to the profiles of three banks with varying factional associations, market, and competitiveness outcomes.

3.3.1 REDACTED

Factions [redacted] is the key figure among the bank's ownership and management, at various points controlling up to 80% of shares in the bank [Banki.ru, 2020]. He used to work for the [redacted] so he fits under the broader definition of *siloviki*. He was also a [redacted]

Outcomes [redacted] incurred 'massive reputational damages' after an episode of *maski-show* [Belton, 2012], prompting [redacted] responsible for the report report on alleged embezzlement which led to the raid. [redacted] regained its competitive position in the market as a result of [redacted] efforts in the courts, but was nonetheless eventually sold off to an organisation directly affiliated with [redacted] calls himself a 'system oligarch' in his book detailing [redacted]

3.3.2 REDACTED

Factions The vast majority of media mentions for bank *regn.* [redacted] [Banki.ru, 2011], appear to have no factional association, apart from its connection to its former [redacted] owner who is now in [redacted] and the [redacted] who appears to be associated, at different points in time, with the finance lobby, the government, the presidential administration, and the resource lobby. The context of mentions appears to be solely focused on alleged financial misconduct: the Bank of Russia accuses [redacted] of siphoning off bail-out funds provided by the Central Bank for own uses to sham trusts, claims which appear to have some basis in fact, according to [redacted] alleges, on the other hand, that he is being pursued for political reasons and [redacted]

Outcomes The bank's licence was revoked in [redacted] after a few episodes of *maski-show*. The ASV is pursuing [redacted] internationally for [redacted] in damages.

3.3.3 REDACTED

Factions [redacted] is part-owned by [redacted] Its main line of business is [redacted] Almost all factional mentions in both the media and ownership statements mention [redacted] and some individuals involved in the day-to-day management of the bank who have government, presidential, and parliamentary associations.

Outcomes The bank retains its competitive position and keeps operating with [redacted]

Chapter 4

Discussion

This section summarises and contextualises the findings presented in chapter 3 on page 18, discussing their broader implications for the field of Russian political economy.

Table 4.1: Quantitative analysis: a summary

Independent variable	Dependent variable			
	Profit	Assets	Profitability	Revoked?
FMI	+	+	not statistically significant	-
FOI	not statistically significant	+	-	+
Efficiency	-	-	not statistically significant	not statistically significant
Competitiveness	+	not statistically significant	+	not statistically significant
Profit	n/a	n/a	+	not statistically significant
Assets	+	n/a	+	not statistically significant
Profitability	+	+	n/a	not statistically significant
Risk level	+	-	+	+
Revoked?	not statistically significant	-	not statistically significant	n/a
siloviki	not statistically significant	not statistically significant	not statistically significant	-
Government & President	not statistically significant	not statistically significant	not statistically significant	+

Table 4.1 on page 29 groups together the results of various quantitative models for bank assets, profit, profitability, and business survival. Clearly, the initial hypothesis of factional association affecting bank survival and financial success bears out, as all but two coefficients are statistically significant. The direction of such a relationship varies based on the dependent variable under consideration. For factional media association we observe that the higher a bank's FMI, the higher its assets and profits, and the lower its likelihood of business termination. On the other hand, higher factional ownership indicates higher total assets but lower profitability, and a higher likelihood of licence revocation or dissolution. For factions that have a statistically significant relationship with these variables, Government & President and *siloviki*, financial indicators are not determined by factional ownership, but business survival is: the *siloviki* lower a bank's odds of business termination, whereas technocratic faction ownership increases those odds. As other factions did not show significant inflense over financials, they are not included in the summary.

It is surprising that associations with the oligarchy have no marked influence over the financials and the odds of business termination. This lack of well-defined influence may partially be explained by the variegated nature of their other factional associations, business conduct, and political views: [redacted] may, on the one hand, present a credible threat to the dominant political regime, and on the other, may simply be a runaway embezzler with no other clear factional associations; whereas the 'system oligarchs' may be pliable, be part of larger patronage networks or have other associations, like [redacted]s intelligence background or [redacted]s connections within the Presidential Administration. Oligarchs may have ambiguous effects on bank survival and financial performance, but associations with the government and the *siloviki* certainly do affect the odds of survival.

This study points future scholarship to develop models of bank-state ownership ties at the individual level, prompting questions about possible conflicts of interest within the government and the security services that control such banks not indirectly through overt and declared state ownership, but via informal networks that may allow them to channel resources bank resources for personal use. Such models may further the understanding of Russian corruption networks which have been studied extensively, but only via the qualitative lens [Cheloukhine & King, 2007, Ledeneva, 1998, Ledeneva, 2002]. The data this paper develops and points to may also help deepen the understanding of Russia's shadow banking sector and put some hard data behind all conjectures and imprecise personal accounts [Nesvetailova, 2018].

The data set developed in this paper may also provide a template for studying factional associations in other countries' banking systems, or even other industries. Some shortcomings of this paper include its lack of a qualitative focus on the individual circumstances facing each bank. Considering the volume of data work already completed for this project and the fact that all scenarios in which banks face licence revocation are largely similar, such an approach is justified. There are, however, further avenues of research on state-bank interactions that could benefit from interview-based inquiry: for example, detailing the processes used to bring about financial misconduct investigations and bank shutdowns.

Conclusion

As [Shih, 2007] says in the title of his book, factions matter. Russian banks are inevitably linked to the state, specifically to the *siloviki*, the government, and the presidential administration. Greater factional media association may result in better financial performance and a lower likelihood of business failure, whereas greater factional ownership seems to increase the odds of licence revocation and decrease profitability. Factional association seems to be an overall more reliable predictor of financial performance and bank survival than do bank competitiveness and efficiency.

This work, admittedly, may pose more questions than it answers, but it is hoped that, with the impetus of a comprehensive data set, future works in the area will bring more granular and precise illustrations of factional influence in Russian banking. Future research may focus on quantifying the power of networks and qualifying their influence on decision-making in banks and in oversight bodies.

Tables

Table 2: Number of name mentions by faction and news source.

Source	State Duma	Finance lobby	Intelligence	Law enforcement	Officer	Oligarchs	President	Regional	Resource lobby	Technocrats	No faction
1prime	1314	378	362	1190	1304	2450	1492	2396	148	1096	7498
asn-news											10
banki	6858	3638	1200	9664	6238	17770	10420	18932	1696	9104	122028
bankir	6	4		12		12	12	20		12	44
belta		4		12		12	12	12		12	6
bfm		2		6		6	6	6		6	30
business-gazeta											52
c-inform											24
cnews											24
finanz											6
finmarket											2
forbes	34	16		48		48	48	56		48	854
gazeta	22	22		42	18	116	74	112	20	42	520
interfax											34
itar-tass	16	26	8	48	20	92	68	80	14	48	352
izvestia	578	68	200	386	650	638	320	670	26	294	2270
kommersant	850	250	196	738	1040	1554	894	1662	150	622	14074
lenta	24	2	10	16	28	22	10	24		12	76
marker	32				24	40		24			278
mskagency		4		12		12	12	12		12	44
other	22	6		6	22	64	42	62	14	6	812
prime		4		12		18	12	12	2	12	6
prime-tass	24	2	10	16	28	22	10	24		12	40
rapsinews	848	228	242	492	812	1526	348	1632	336	326	9734
rbc	482	214	142	598	296	992	638	966	102	576	7966
rbcdaily	112	36	28	82	122	260	120	236	26	78	1596
reuters	140	28	52	108	78	184	148	210	18	108	790
rg											42
ria	950	482	84	1358	842	2662	1896	2580	148	1350	5588
rian	4	4		6	6	12	6	12		12	168
rns	336	86	8	210	134	696	460	618	38	210	1990
tass	952	534	148	1436	876	3080	2366	2920	244	1490	6570
vedomosti	922	234	142	652	778	1524	956	1728	156	538	14048
vestifinance											28
vestipk											10

Code

Listing 1: scraPy web crawler for *Lobbying.ru*

```
import scrapy
from urllib.parse import urljoin
import pandas as pd

df = pd.read_csv('lobbyist_links_cats.csv')
urls = df['name_link'].astype(str).tolist()

class LobbyingSpiderItem(scrapy.Item):
    name_link = scrapy.Field()
    name = scrapy.Field()
    person_bio = scrapy.Field()
    categories_text = scrapy.Field()
    categories_links = scrapy.Field()
    bio_html = scrapy.Field()
```

Table 3: Influence of granular factional ownership on the odds of licence revocation

	(1) Revoked?	(2) Revoked?	(3) Revoked?	(4) Revoked?	(5) Revoked?	(6) Revoked?	(7) Revoked?	(8) Revoked?	(9) Revoked?
Revoked?									
Oligarchs	-1394.6870*	-1558.4471*	-1572.5966*	193.6040	62.7278	1622.0333	535.6423	2194.1265	1621.2433
	(-2.22)	(-2.37)	(-2.37)	(0.15)	(0.05)	(0.84)	(0.26)	(0.97)	(0.69)
Officer	1534.9832*	1109.1711	1131.6232	1191.3130	1280.2964	1296.7375	1299.6079	703.9985	280.9408
	(2.39)	(1.55)	(1.57)	(1.60)	(1.68)	(1.64)	(1.61)	(0.79)	(0.26)
Regional		708.4203	805.7997	902.8115	1302.9053	1155.0747	4461.8749*	3262.7695	4565.2928
		(1.56)	(1.36)	(1.43)	(1.34)	(1.18)	(2.20)	(1.61)	(1.68)
President			-142.7973	-180.9926	-657.2783	-389.6119	-3692.0628	-3293.0859	-2792.9490
			(-0.27)	(-0.31)	(-0.64)	(-0.37)	(-1.79)	(-1.63)	(-1.29)
No faction				-1868.3712	-2235.2081	-3646.1194	-6019.0943*	-7932.8311**	-6871.3264*
				(-1.64)	(-1.71)	(-1.89)	(-2.37)	(-2.85)	(-2.35)
Intelligence					507.4255	2565.0560	420.0871	-534.3515	99.7828
					(0.55)	(1.24)	(0.20)	(-0.25)	(0.04)
Law enforcement						-2357.1385	-1141.4923	-1495.6564	-2355.4346
						(-1.17)	(-0.60)	(-0.80)	(-1.12)
Finance lobby						-13989.1063	-11821.9832	-11787.5428	-11400.8529
						(-0.61)	(-0.51)	(-0.51)	(-0.50)
Resource lobby							4353.8802*	5258.6926*	4992.2824*
							(2.02)	(2.38)	(2.07)
State Duma								2028.9161*	631.2141
								(1.99)	(0.33)
Technocrats									0.0000
									(.)
Constant	0.3358***	0.3383***	0.3372***	0.3582***	0.3629***	0.3640***	0.3688***	0.3741***	0.3553***
	(4.28)	(4.30)	(4.28)	(4.48)	(4.51)	(4.52)	(4.58)	(4.64)	(4.38)
Pseudo R^2	0.009	0.012	0.012	0.015	0.016	0.018	0.024	0.029	0.030
Observations	714	714	714	714	714	714	714	714	707

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

```
class LobbyistSpiderSpider(scrapy.Spider):
    name = 'lobbyist_spider'
    allowed_domains = ["web.archive.org"]
    start_urls = urls
    def parse(self, response):
        item = LobbyingSpiderItem()
        item["name"] = response.css("h1::text").extract()
        item["name_link"] = response.request.url
        item["person_bio"] = ' '.join(map(str.strip,
           response.css("div.persons_blocks ::text").
           extract()))
        item["categories_text"] = ' '.join(map(str.strip,
           response.css("div.txt-box2 ::text").extract()))
        item["categories_links"] = ' '.join([urljoin("http
           ://web.archive.org",link) for link in  response
           .css("div.txt-box2 a::attr(href)").extract()])
        item["bio_html"] = ' '.join(map(str.strip,
           response.css("div.persons_blocks").extract()))
```

```
        yield item
```

Listing 2: scraPy web crawler for downloading *CBR.ru* ownership statements in *.pdf*

```
import scrapy
from urllib.parse import urljoin

class BankInfluenceItem(scrapy.Item):
    file_urls = scrapy.Field()
    files = scrapy.Field()

class BankInfluenceSpider(scrapy.Spider):
    name = 'bank_influence'
    allowed_domains = ['cbr.ru']
    start_urls = ['http://www.cbr.ru/VFS/credit/depend/']

    def parse(self, response):
        for link in response.css('pre␣a␣::attr(href)').
           extract():
            file_urls = [urljoin('http://cbr.ru', link)
               for link in response.css('pre␣a␣::attr(href
               )').extract()]
            yield BankInfluenceItem(file_urls=file_urls)
```

Listing 3: Text extraction and named entity recognition for *CBR.ru* ownership statements in *.pdf*

```
from pdfminer.layout import LAParams
from pdfminer.converter import PDFPageAggregator
from pdfminer.pdfpage import PDFPage
from pdfminer.layout import LTTextBoxHorizontal

from pdfminer.pdfparser import PDFParser
from pdfminer.pdfdocument import PDFDocument
from pdfminer.pdfpage import PDFPage
from pdfminer.pdfpage import PDFTextExtractionNotAllowed
from pdfminer.pdfinterp import PDFResourceManager
from pdfminer.pdfinterp import PDFPageInterpreter
from pdfminer.pdfdevice import PDFDevice
import pandas as pd
import re
from tqdm import tqdm
import os

from natasha import (
    Segmenter,
```

```
    MorphVocab ,

    NewsEmbedding ,
    NewsMorphTagger ,
    NewsSyntaxParser ,
    NewsNERTagger ,

    PER ,
    NamesExtractor ,
    DatesExtractor ,
    MoneyExtractor ,
    AddrExtractor ,

    Doc
)

segmenter = Segmenter ()
morph_vocab = MorphVocab ()
emb = NewsEmbedding ()
morph_tagger = NewsMorphTagger (emb)
syntax_parser = NewsSyntaxParser (emb)
ner_tagger = NewsNERTagger (emb)
names_extractor = NamesExtractor (morph_vocab)

influence_text = pd.DataFrame (columns=['regn','date', '
   text'])
regns1 = []
dates1 = []
texts = []

influence_names = pd.DataFrame (columns=['regn', 'date', '
   name', 'name_lemma'])
regns2 =[]
dates2 = []
names = []
names_lemma = []

influence_orgs = pd.DataFrame (columns=['regn', 'date', '
   org', 'org_lemma'])
regns3 =[]
dates3 = []
orgs = []
orgs_lemma = []

files = os.listdir ('.')
```

```python
for fn in tqdm(files):
    if fn.endswith('.pdf'):
        print("NEW_DOCUMENT")
        #EXTRACT TEXT FROM .pdf
        document = open(fn, 'rb')
        #Create resource manager
        rsrcmgr = PDFResourceManager()
        # Set parameters for analysis.
        laparams = LAParams()
        # Create a PDF page aggregator object.
        device = PDFPageAggregator(rsrcmgr, laparams=laparams)
        interpreter = PDFPageInterpreter(rsrcmgr, device)

        regn = fn[2:6]
        print("REGN OF REPORT "+regn)
        date = fn[7:11]+"/"+fn[11:13]+"/"+fn[13:15]
        print("DATE OF REPORT "+date)
        text = []
        for page in PDFPage.get_pages(document):
            interpreter.process_page(page)
            # receive the LTPage object for the page.
            layout = device.get_result()
            for element in layout:
                try:
                    text_bits = element.get_text().replace("\n", " ").replace("\t", " ").strip()
                    text.append(text_bits)
                except:
                    pass
        text = " ".join(text)
        print(text)
        texts.append(text)
        dates1.append(date)
        regns1.append(regn)

        #PREPROCESS TEXT FOR ANALYSIS
        doc = Doc(text.strip().replace("   ", " ").replace("  ", " "))
        doc.segment(segmenter)
        doc.tag_ner(ner_tagger)
        [span.normalize(morph_vocab) for span in doc.spans]
```

```
        #RECOGNISE NAMES IN TEXT, LINK TO REGN
        name = [span.normal for span in doc.spans if span.type == 'PER']
        names.extend(name)

        for n in name:
            regns2.append(regn)
            dates2.append(date)
        name_lemma = [morph_vocab.lemmatize(n, 'PROPN', feats={'Animacy': 'Anim', 'Gender': 'Fem', 'Number': 'Sing'}) for n in name]
        names_lemma.extend(name_lemma)

        #RECOGNISE ORGANISATIONS IN TEXT, LINK TO REGN
        org = [span.normal for span in doc.spans if span.type == 'ORG']
        orgs.extend(org)
        org_lemma = [morph_vocab.lemmatize(o, 'PROPN', feats={'Animacy': 'Anim', 'Gender': 'Fem', 'Number': 'Sing'}) for o in org]
        orgs_lemma.extend(org_lemma)
        for o in org:
            regns3.append(regn)
            dates3.append(date)

influence_text['date'] = dates1
influence_text['regn'] = regns1
influence_text['text'] = texts
print(influence_text)
influence_text.to_csv('influence_text.csv')

influence_names['date'] = dates2
influence_names['regn'] = regns2
influence_names['name'] = names
influence_names['name_lemma'] = names_lemma
print(influence_names)
influence_names.to_csv('influence_names.csv')

influence_orgs['date'] = dates3
influence_orgs['regn'] = regns3
influence_orgs['org'] = orgs
influence_orgs['org_lemma'] = orgs_lemma
print(influence_orgs)
influence_orgs.to_csv('influence_orgs.csv')
```

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