Research Proposal: The Revolving Doors of Financial Regulators

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Abstract: This paper studies the rulemaking process of financial regulation by examining more than 100,000 public comment letters, numerous meeting records between banks and regulators, and a comprehensive database of employees in regulatory agencies. We test whether the revolving door between the regulatory agencies and the private sectors distort the incentive of the regulators in the rulemaking process.

Between 2010 to 2013, Mrs. Tram Nguyen worked for the SEC as a financial regulator, earning $180K a year, a modest salary compared to her classmates at Columbia Law School. At the SEC, she led the development and implementation of the new rules under the Dodd-Frank and JOBS acts for private fund advisers. For instance, on 2011, she composed Rule RIN 3235-AK81, a rule exempts certain asset advisors for certain regulations, as one of the three main writers of the rule. Two years later, she quitted her job and got hired by a top law firm, Mayor Brown, as a partner, earning $600K a year. She has been recognized as "Hedge Fund Compliance Attorney of the Year" by *Global Law Experts*.

This is one example of the much debated "revolving door" in banking regulation identified by our database on financial regulators and the regulations written by them. In this project, we try to shed some light on the underlying mechanism of the "revolving door" phenomenon by leveraging machine learning and big data. We analyze the rulemaking process by analyzing the changing of text of financial regulations from proposals to the final rules and trace these changes to the comment letters from the private sectors and the meetings between regulators and the private sectors. We analyze the career paths of the writers of these rules by combing salary databased of regulatory-agency employees and social networks of professionals online.

We test two main hypothesis driving the revolving doors. The first hypothesis is the "quid pro quo" view, which suggests that regulators soften regulations as a favor to the banks to exchange for future career opportunity. We test this view by examining whether the rulemakers are more

likely to cite comments from their future employers, conditional on them being employed by the industry. The second hypothesis is "regulatory schooling" view, which suggests that regulators write complex rules so that they can leverage they can capitalize their knowledge on this rule for their later career in the private sector. We test this view by examining whether the rulemakers of complex rules are more likely to quit their jobs in the regulatory agencies and being hired by private sectors, and conditional on switching to the private sector, whether the rulemakers of complex rules experience a greater salary increase.

To answer these questions, we build a novel database using Python to scrape and analyze textual information. Specially, we scape the text of rules proposed by five government agencies under the Dodd-Frank Act including the SEC, the Federal Reserve Board, the OCC, the FIDC, and the CFTC. We identify the rulemakers in the cover page of the rule. We also collected by the comment letters made by banks and the meeting logs between regulators and banks from the websites of these agencies and from the Federal Register, which is made public by the Administrative Procedure Act.

After we have collected the rules, we make several textual analyses of the rules using Python. First, we analyze the complexity of the rules and give each one a Flesch–Kincaid readability score. This is used in the first main test to determine the complexity of the regulations. Then, we employ the Smith–Waterman algorithm, which is widely used in biology to compare the likeness of genes, to determine which comments are cited in the final version of the rule. This is used in the second main test to see if the rule makers have given any preferential treatment to their future employers.

The second part of the database will include personal information about the rule makers, notably their employment transition records and salary. To collect employment information, we use Python to scrape and parse publicly available sources like LinkedIn, Thomson Reuters News Archive, and lobbying disclosure forms. We rely on salary websites such as Salary.com and Glassdoor for private positions, and federalpay.org for public positions. We also collect their personal characteristics such as age and educational background, where possible.