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DEPUTIZATION

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ABSTRACT

A policy of deputization asks agents to monitor others without providing explicit incentives. It is often used to prevent dangerous activities. To calibrate whether and why it works, we study recent laws that deputized financial professionals to help fight elder financial abuse. We show deputization led to a 4%-6% decrease in suspected cases and a 4.5% drop in personal bankruptcies. Women, minorities, and unmarried people benefited more. Effectiveness operated through higher community-mindedness and deeper social connections. Egoistic incentives, legal concerns, publicity, and religiosity were less important. This suggests that regulators can rely on social networks to solve tough problems.

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1. Introduction

Deputization occurs when a principal empowers an agent to carry out a monitoring function without providing explicit incentives. Because of its permissive nature, the success of this policy depends on other existing extrinsic incentives or intrinsic motivation (moral beliefs, ethical behavior, or a sense of community).[1] Deputization may be useful when the principal lacks a sufficient revenue stream to provide monetary incentives or the scale of the task makes it infeasible to completely reward or punish the agents who participate.

Deputization is frequently important for solving public goods problems that involve identifying dangerous activities. For example, the federal government calls upon UPS and FedEx to identify suspicious packages associated with drug trafficking or terrorist activity (Michaels, 2011). Financial institutions are asked to monitor transactions for money laundering, fraud, and other crimes (Levinson, 2008). Facebook and Google assist in flagging communications that are suspicious for terrorism or other illegal activities (Michaels, 2018).

Deputization may also involve individuals. For example, New York City recently deputized thousands of social distancing ambassadors to curb the spread of COVID-19 amid growing social unrest.[2] It has also been applied to reporting suspicious activities at airports, identifying illegal immigration (Lin, 2009), and stopping the abuse of minors (Kesner, 2002; Mitter, 2011).

Opportunities to calibrate whether and why deputization works are rare because it is not typically implemented for exogenous reasons. In this paper, we exploit a quasi-natural experiment that involved a nationwide effort to curb financial abuse of the elderly. This is not only a pervasive and growing problem, it is pernicious.[3] Elder abuse is hard to police because the perpetrators are often people close to the victim like family members and caregivers.

Through the Model Act and FINRA Rule 2165, regulators deputized financial professionals and gave them the authority to halt the disbursement of funds that appear suspicious for financial abuse. Both regulations are permissive rather than mandatory. Regulators chose

[1] Many economists have suggested that agents conform to ethical codes rather than act egoistically (e.g. Arrow, 1988; Brennan, 1994; Akerlof, 2007) As far back as Aristotle (in Nicomachean Ethics), it was proposed that individuals in a civilized society incorporate ethical standards into the decisions that they make (Aristotle, 2004). This has been studied in psychology (Judge and Ilies, 2002), law (Shavell, 2002), economics (Frank, 1987; Noe and Rebello, 1994), and finance (Carlin and Gervais, 2009). See Carlin et al. (2009) and Sapienza et al. (2013) for an analysis of trust formation in markets.

[2] See https://newyork.cbslocal.com/2020/05/10/social-distancing-ambassadors/.

[3] According to the Consumer Financial Protection Bureau (CFPB), in 2017 there were 63,500 cases of elder financial exploitation reported to the Department of the Treasury, totaling $1.7 billion dollars. See https://files.consumerfinance.gov/f/documents/cfpb_suspicious-activity-reports-elder-financial-exploitation_report.pdf. DeLiema et al. (2020) find that 30% of older Americans have experienced others using or attempting to use their accounts without permission.

not to give participants rewards or make them subject to punitive actions if they choose not to act. As FINRA Regulatory Notice 17-11 states: "The rule creates no obligation to withhold a disbursement of funds or securities in [suspicious] circumstances." Importantly, these rule changes did not alter the existing requirement that financial professionals report elder financial exploitation to the U.S. Treasury, as mandated by the *Bank Secrecy Act of 1970*. However, oftentimes retrieving the lost monies after disbursement was unsuccessful. So, regulators implemented these new rules to allow more time for investigation, but did not include carrots or sticks.

We exploit the staggered passage of these rules across states to identify whether deputization works and why. This setting is natural for a staggered difference-in-differences specification with multiple control groups (Goodman-Bacon, 2018) and provides a unique opportunity to assess this type of policy change. The timing of adoption across states is unrelated to previous financial exploitation, the size of the elderly population, and other observable characteristics. To discern the channels through which this regulation acts, we examine how effectiveness of the laws varies at the county level.

We amass a large dataset: reports of suspected elder financial exploitation from the Department of Treasury[4], the employment history of the entire universe of registered brokers and advisers from FINRA and the Securities and Exchange Commission (SEC), credit bureau reports from older adults in the United States, county-level data on congregations and adherents from the U.S. Religion Census, media coverage for elder abuse during 2015-2020 from Factiva, and county-level data from the U.S. census.

Deputizing appears to be effective at deterring the financial exploitation of the elderly. We estimate that this policy led to a 4%-6% reduction in the monthly number of elder financial abuse cases in treated counties. We find similar estimates using a sample of counties that are matched on pre-treatment characteristics. This effect is more pronounced for women, minorities, seniors without a spouse, and seniors with more retirement capital, who are more likely to be targets of financial exploitation.

We investigate the welfare implications of the new laws by assessing their effect on personal bankruptcies. Consumer bankruptcy is well-known to result in substantial damages to individuals and a dead-weight loss to society (e.g. Athreya, 2002; Chatterjee and Gordon, 2012). We find that this policy of deputization was responsible for a 4.5% reduction in the frequency of personal bankruptcies among the elderly, which is a substantial welfare effect.

A series of cross-sectional tests suggest that higher community mindedness and social

[4] A CFPB report studying a random sample of suspected cases finds that approximately 80% result in a financial loss. See https://www.justice.gov/file/852856/download.

connectedness are responsible for the success of deputization. Other alternatives such as preserving fees based on assets under management (AUM), getting publicity[5], adhering to moral codes, or using the law to strengthen desirable norms (Sunstein, 1996) do not appear to be channels through which the new regulations affected outcomes.

We find that there is a significant reduction in elder exploitation in counties that have a higher per capita presence of investment advisers. But, the same is not true for brokers. This dichotomy casts doubt on several potential explanations for the overall drop in elder abuse. If financial incentives or legal ramifications were important, then we should likely see an effect for *both* sets of professionals.

To explore these egoistic incentives, we show that when more professionals in a county charge fees for AUM, commissions, or hourly fees, this does not change the effectiveness of the new laws. Also, the laws did not appear to primarily curb improper behavior by the financial professionals themselves: we find no difference in the effectiveness of the laws in counties with more past customer complaints, regulatory actions, civil litigation, or criminal actions. Moreover, there was no change in regulatory actions or measures of adviser and broker misconduct after the implementation.

The dichotomy is more likely to be based on the quality of relationships, as investment advisers typically work closely with clients and brokers are at arm's length. We find that the reduction of elder abuse is higher for advisers who have spent more time in a community. The same is not true for differences in time in the profession or tenure at a firm.[6] Also, the reduction appears weaker when financial professionals are registered to work in multiple states, perhaps because their clients are more dispersed. These findings imply that stronger bonds may be more important for deputization to work than experience or skill.

Consistent with this, deputization appears to work better in areas that have more social connectedness. We find a greater reduction in elder exploitation in communities with larger religious congregations, controlling for the number of adherents per capita. Advisers within more dense social networks may be more community minded or interested in preserving their local reputations. By contrast, more religious counties with more adherents per capita do not see a differential change in elder abuse. This difference makes a moral imperative a less likely explanation for the success of deputization.

The role of social networks in regulatory design has been underappreciated. One of the

[5]Publicity results from media coverage across communities. An extensive Factiva news search suggests there is essentially no coverage of elder financial exploitation using a firm's or adviser's name, casting doubt on a publicity-seeking incentive to serve clients.

[6]Tenure at a firm does not guarantee deep-seated relationships. Clients are portable when advisers change firms and promotion that comes with tenure may even reduce time with clients because of added administrative responsibilities (Clifford and Gerken, 2017).

contributions of our paper is to show that regulators should consider and can rely on social networks and community-mindedness when enacting permissive policies like deputization.[7] Existing literature sheds light on why social networks and the strength of relationships are likely to matter for deputization to work. First, more connected communities and personal relationships may help financial professionals identify unusual activity. Second, professionals in such communities are more likely to derive utility from the increases in welfare of others (Leider et al., 2009). Third, social norms and morality may only be applicable to a narrow community, such as a congregation (Tabellini, 2008). Fourth, reciprocal exchange is more likely to be important in closer-knit communities, which creates incentives to protect clients (Kranton, 1996).

It is important to point out that the magnitudes of the effects of deputization in this paper likely underestimate its potential role in other settings. First, from an econometric standpoint, the fact that the policy's effect is not immediate works against finding an effect in a staggered difference-in-differences specification. We describe this in detail in the paper. Second, the financial industry is not known for being particularly altruistic. A growing literature characterizes this (Dimmock and Gerken, 2012; Dimmock et al., 2018; Charoenwong et al., 2019). In fact, financial professionals are commonly culpable for preying on the elderly (Egan et al., 2019). Happily, though, we do find in this paper that relying on financial professionals does work, which may cast a more positive, optimistic light on the industry.

2. Background

2.1. Elder Financial Exploitation

Elder financial exploitation is defined by the U.S. Government Accountability Office as the "illegal or improper use of an older adults funds, property, or assets."[8] Such exploitation is pervasive and economically meaningful. In 2017, there were 63,500 cases of elder financial exploitation reported to the Department of the Treasury, totaling \$1.7 billion dollars.[9] These numbers likely represent a lower bound because of under-reporting: the National Adult Protective Service Association (NAPSA) estimates that for every 1 case of elder abuse that comes to light, another 43 remain hidden.[10]

[7] Review of comment letters shows no consideration of these community dimensions when the Model Act and FINRA Rule 2165 were designed. Comment letters available at https://www.nasaa.org/nasaa-proposals/?t=seniors&y=.

[8] See https://www.gao.gov/new.items/d11208.pdf.

[9] See https://files.consumerfinance.gov/f/documents/cfpb_suspicious-activity-reports-elder-financial-exploitation_report.pdf.

[10] See https://www.napsa-now.org/get-informed/exploitation-resources/.

Why are the elderly particularly vulnerable to financial exploitation? Two interrelated sets of factors are at work. The first set is health-related. The aging process brings about cognitive and physical changes that elevate the risks of financial exploitation. The changes can include cognitive impairment, poor physical health, functional impairment, and dependency on others. According to the Alzheimers Association, around 15-20% of people 65 years of age or older have Mild Cognitive Impairment (MCI), and about a third of persons with MCI develop dementia within five years.[11]

The second set of factors are related to financial and retirement trends. Americans over the age of 50 currently account for 77% of financial assets in the United States.[12] Their wealth, combined with greater financial autonomy upon retirement brought by a general shift from defined benefit to defined contribution plans, makes them popular targets of financial exploitation. This issue will likely become more prevalent as the elderly population grows in the next 40 years.[13]

Elder financial exploitation can be divided into three broad categories: scams by strangers, scams by professionals, and exploitation by family members and trusted others. Typical scams by strangers include lottery scams, "grandparent" scams (for example, an older adult is called and told that his or her grandson is in jail and needs money immediately), and charity scams (i.e. falsely soliciting funds for good causes). Scams by professionals include predatory lending, annuity schemes, Medicare scams, and identity theft (e.g. fraudulently opening a credit card in an elder person's name). Common ways family members exploit older adults include stealing checks, exploiting joint bank accounts, withholding assets from needed care and medical services, and threatening to abandon or harm unless the older person transfers money.[14]

The CFPB's analysis of a random sample of 1,051 elder financial exploitation cases revealed that 51% are perpetrated by strangers, 36% by family members, 25% by caregivers, and 7% by fiduciaries. Around 80% of cases resulted in financial loss. Both the probability and the amount of the losses are substantially higher when the perpetrator is a known person ($83,600) rather than a stranger ($17,000). In 7% of cases, the loss exceeded $100,000. These magnitudes are meaningful for most retirees. In addition, female, African American,

[11] https://www.alz.org/media/documents/alzheimers-facts-and-figures-2019-r.pdf.

[12] https://www.justice.gov/file/1125706/download.

[13] Adults that are above 65 years old is projected to grow from 15.2% of total population to 23.4% by 2060. See https://www.census.gov/library/stories/2018/03/graying-america.html.

[14] For the purpose of this paper, we use the term "elder financial exploitation" and "elder financial abuse" interchangeably. However, some definitions might distinguish between two types of elder financial exploitation: financial abuse, in which a relationship of trust has been violated by family members, friends, or others; and elder fraud, such as scams perpetrated by strangers.

Latino, poor, and isolated older adults were disproportionately victimized.[15]

2.2. Investment Advisers and Brokers

In the United States, firms known as registered-investment advisers (RIAs) employ investment-adviser representatives (IARs). The Investment Advisers Act of 1940 defines an investment adviser broadly as "Any person who, for compensation, engages in the business of advising others, either directly or through publications or writings, as to the value of securities or as to the advisability of investing in, purchasing, or selling securities, or, who for compensation and as part of a regular business, issues or promulgates analyses or reports concerning securities."

The SEC regulates investment advisers. RIAs and IARs have a fiduciary duty to their clients. Clients include individuals, high-net-worth persons, pooled-investment vehicles (e.g., hedge funds, and mutual funds), pension funds, and governments. Common names for investment advisers include asset managers, investment counselors, investment managers, portfolio managers, and wealth managers.

FINRA oversees brokers. The Securities Exchange Act of 1934 defines a broker as "any person or company engaged in the business of buying and selling securities on behalf of its clients, for its own account (as dealer), or both." Brokers typically receive commissions and product fees, whereas investment advisers earn fees based on hours of service and assets under management (AUM). Also, brokers are held to a weaker suitability standard, which requires a broker to take into account a client's financial situation and investment needs, but does not require that they put the client's interests before their own. Because of different forms of compensation and fiduciary duty, the conflicts of interest are potentially higher for brokers than advisers.

Approximately 50% of broker representatives are dual-registered as investment advisers and about 80% of investment adviser representatives are also registered as brokers. A commonly expressed concern by regulators is that clients may not be able to determine whether an individual is operating as an investment adviser with a fiduciary standard or as a broker, especially because brokers are often referred to as financial advisers. In the remainder of the paper, we will make this distinction carefully in our analysis.

3. Legislation Protecting Elders

We study two regulatory changes that granted financial professionals the power to halt disbursements of funds that they deemed suspicious. Both rules did not provide explicit

[15] See https://www.justice.gov/file/852856/download.

incentives that required participation. Before these rules were passed, professionals were required to report suspicious behavior. But, because monies were often hard to recover during investigations, simple reporting did little to limit financial loss.[16] The two rules vary in terms of their implementation and the types of financial professionals covered. These differences are summarized in Table 1 and detailed below.

3.1. The Model Act

The North American Securities Administrators Association (NASAA) is a self-regulatory organization made up of state and provincial securities regulators from the United States, Canada, and Mexico. NASAA drafts model rules that guide various state and provincial legislatures. The *NASAA Model Legislation or Regulation to Protect Vulnerable Adults from Financial Exploitation* (hereinafter, "Model Act") originated as an initiative of the NASAA's Committee on Senior Issues and Diminished Capacity. On September 29, 2015, a draft of the Model Act was released for a 30-day public comment period. On January 22, 2016, NASAA members voted to approve the Model Act.

The NASAA Model Act applies to both broker-dealers and registered investment advisers, including certain qualified employees (e.g. broker-dealer agents, investment adviser representatives, and persons serving in a supervisory, compliance, or legal capacity for a broker-dealer or investment adviser). The key provision that enhances the ability of these financial professionals to protect the elderly is the authority to delay disbursements of funds. Broker-dealers and investment advisers may delay disbursement of funds from a senior's account for up to 15-25 days if they reasonably believe that such disbursement will result in the financial exploitation of the senior.[17] The broker-dealer or investment adviser halting the disbursement must direct that the funds be held in temporary escrow pending resolution of the disbursement decision.

The ability to delay a disbursement of funds allows for an investigation to occur prior to any loss of funds due to exploitation. If a disbursement is delayed, the broker-dealer or investment adviser must initiate an internal investigation of the suspect disbursement and provide the results of such investigation to the state securities administrator and Adult

[16]See interview with Michael Pieciak (Deputy Commissioner, Vermont Securities Division, NASAA) during the SEC Meeting of the Advisory Committee on Small and Emerging Companies.

[17]The Model Act defines financial exploitation as "the wrongful or unauthorized taking, withholding, appropriation, or use of money, assets or property of an eligible adult, or any act or omission taken by a person, including through the use of a power of attorney, guardianship, or conservatorship of an eligible adult, to: i. Obtain control, through deception, intimidation or undue influence, over the eligible adults money, assets or property to deprive the eligible adult of the ownership, use, benefit or possession of his or her money, assets or property; or ii. Convert money, assets or property of the eligible adult to deprive such eligible adult of the ownership, use, benefit or possession of his or her money, assets or property."

Protection Services (APS) agencies. At the discretion of the state securities regulator or APS agencies, the broker-dealer or investment adviser may extend the delay for an additional 10 days if necessary.

We identify state-level acts, laws, statutes, and regulations that are based on the Model Act or contain similar provisions to the Model Act across U.S. states. For each state, we obtain the name of the relevant legislation or regulations, the passage date, and the effective date from the state's legislature website.

As shown in Table 2, as of September 2019, 25 states have enacted legislation that contains many of the provisions found in the Model Act. Prior to the passage of the Model Act in 2016, three states—Delaware, Missouri, and Washington —already enacted laws that contain provisions similar to the Model Act.[18] Following the passage of the Model Act in January 2016, three states —Alabama, Indiana, and Vermont —adopted laws based on the Model Act. Following that, ten states adopted these laws in 2017, six states in 2018, and four states in 2019. Figure 1 Panel A shows graphically the staggered adoption of the Model Act or similar provisions across U.S. states.

Although state-level legislation was often inspired and guided by the Model Act, states exercised autonomy in determining the exact scope of the legislation. For example, 15 states required mandatory reporting of suspected financial abuse cases to state APS offices just as required by the Model Act, whereas 11 states made this reporting voluntary. In addition, although the majority of the states enacted regulations that applied to broker-dealers and investment advisers, five states expanded the scope to include all financial institutions and one state limited the scope to include only broker-dealers.

3.2. FINRA Rule 2165

State regulation of broker-dealers exists in parallel with the Financial Industry Regulatory Authority (FINRA), a federally-sanctioned self-regulatory organization. In March 2017, FINRA adopted Rule 2165, "Financial Exploitation of Specified Adults", that allowed broker-dealers to place temporary holds on disbursements of funds or securities from a senior customer's account when there is a reasonable belief that financial exploitation is taking place.[19] Upon placing a hold, Rule 2165 requires the broker-dealer to immediately initiate

[18] Judy Shaw, the president of NASAA in 2016, commented that the motivation for the Model Act was based on the early experiences Delaware, Missouri, and Washington had with various elements of the Model Act. States adopted the policy in a staggered fashion, which depended on the timing of legislative sessions and capacity. We examine the timing of adoption more completely in Section 5.1.

[19] Jim Wrona, vice president and associate general counsel at FINRA, gave the following example: A client will say, "I won the lottery, but I need to pay the taxes upfront before I can claim the award". If the client demands the money even after the broker has explained that its a scam, he or she can then temporarily pause the disbursement and investigate further.

an internal review of the facts and circumstances.[20] On February 5, 2018, the rule was approved by the SEC and became effective nationwide. The essence of the FINRA Rule 2165 is similar to that of the Model Act, but is distinct in several aspects. A comparison of these two rules is in Table 1.

4. Data and Sample

4.1. Elder Financial Exploitation

We obtained data on elder financial exploitation from the Suspicious Activity Reports maintained by the U.S. Department of Treasury's Financial Crimes Enforcement Network (FinCEN). As established by the federal Bank Secrecy Act of 1970, financial institutions such as banks, registered investment advisers, brokers and dealers, money service businesses, and insurance companies must file Suspicious Activity Reports with FinCEN if they know or suspect that a transaction has no apparent lawful purpose or is not the sort in which the particular customer would normally be expected to engage.[21] The filing is mandatory when a suspicious transaction involves above $5,000 in funds or assets, and voluntary if the transaction is below the such threshold.

In April 2012, FinCEN introduced electronic suspicious activity reporting with a designated category for "elder financial exploitation." We collect variables such as the total number of reported cases in a county in a month, the type of reporting institution, the type of financial product, the instrument of transaction, and the regulatory authority. Reports are tied to the county in which the victim resides.[22] Examples of financial products used are credit cards, debit cards, insurance and annuity products, and securities. Examples of transaction types are funds transfer, checks, and money orders.

Important to our analysis is that the reporting requirements of financial professionals to FinCEN did not change with a state's adoption of the Model Act or with FINRA's adoption

[20] Although the rule applies to the disbursement of securities, it does not apply to transactions in securities. For example, Rule 2165 would not apply to a customers order to sell his shares of a stock. However, if a customer requested that the proceeds of a sale of shares of a stock be disbursed out of his account, then the rule could apply to the disbursement of the proceeds.

[21] See 31 U.S.C. § 5311 et seq. and 31 C.F.R. Chapter X. Criminal penalties can be assessed for willful Bank Secrecy Act regulation violations. Any individual found guilty of this is subject to criminal fines of up to $250,000 or five years in prison, or both. If the individual commits a willful Bank Secrecy Act violation while breaking another law or committing other criminal activity, he or she is subject to a fine of up to $500,000 or ten years in prison, or both. Violations of certain Bank Secrecy Act provisions or special measures can make an institution subject to a criminal money penalty up to the greater of $1 million or twice the value of the transaction.

[22] Counties are defined by zip codes as provided by the filing institution indicating where the suspicious activity occurred.

of Rule 2165.[23]

4.2. Investment Advisers and Brokers

Because the Model Act operates through investment advisers, we obtain individual-level data on investment adviser representatives from the SEC's Investment Adviser Public Disclosure (IAPD) database. Representatives are required to file Form U4 with the IAPD annually or when there are material changes. The data is survivorship-bias free for at least the past ten years. The data includes the firm an adviser works for, the branch office the adviser works in (city, state), and the dates an adviser worked at that branch. Full employment and registration histories are available. Thus, this data allow us to calculate a time series of the per capita number of investment advisers in a county. We also have the date, resolution, and detailed text of each customer complaints filed against an adviser, regulatory actions taken against each adviser, and other disclosures such as criminal proceedings that must be made to clients.

We also obtain data on registered investment adviser (RIA) firms through a Freedom of Information Act filed with the SEC. RIAs are required to file Form ADV annually, which records information such as firm ownership structure, total asset under management, number of employees, clientele composition (individual vs. institution), locations, conflicts of interests, and a variety of disclosures such as customer complaints and regulatory actions. We do not have Form ADV data for RIAs managing less than $100 million because in 2012 Dodd-Frank shifted oversight responsibilities for such advisers from the SEC to the states (Charoenwong et al., 2019).

Because FINRA's rule change and the Model Act both empower broker-dealers and broker representatives, we gathered similar data from the BrokerCheck database that we gathered for investment advisers from the IAPD. We again have the ability to know which firm a broker works for, what branch the broker works in, and for what dates the broker worked there.

Both the IAPD and BrokerCheck are managed by FINRA and thus use the same identifiers for individuals. We can therefore observe which investment adviser representatives are dual-registered as brokers.

4.3. Experian Credit Score Data

To explore the economic consequences of financial exploitation on the senior population, we use a panel dataset of individual credit bureau records from 2012 to 2018. The data

[23] Judy Shaw, the president of NASAA explained to us that "reporting to APS is separate and in addition to FinCen requirements. Some of the state APS reporting requirements have been in place for years, some, like Maine, have been put in place as a result of adoption of the NASAA Model Act."

contain a 1% representative sample of all U. S. residents selected based on the last two digits of their social security number. This sampling procedure produces a random sample of individuals because the Social Security Administration sequentially assigns the last 4 digits of social security numbers to new applicants regardless of geographical location.

The dataset contains detailed individual demographic and economic characteristics, such as age, sex, marital status, dwelling status, credit score, estimated income, and debt characteristics including auto loans, mortgages, credit card debt, and medical debt. For our purposes, we use the subsample of individuals that are above 65 years old to examine the credit market impacts of reduced financial fraud targeted at seniors. This dataset also provides additional information about time-varying county demographic and economic trends that are difficult to obtain from other data sources. We construct control variables such as county average debt-to-income ratio, average credit score, fraction of subprime borrowers, and fraction of married population.

4.4. U.S. Religion Census

We use data from the 2010 U.S. Religion Census to measure the number of religious adherents and religious congregations in each county. Every 10 years, the Association of Statisticians of American Religious Bodies (ASARB) compiles data from national surveys on religious affiliation in the United States. Based on the results from these surveys, the ASARB prepares the "U.S. Religion Census: Religious Congregations and Membership Study", which reports county-by-county data on the number of congregations and total adherents by religious affiliation.[24] These proxies for religiosity are standard in the literature (Hout and Greeley, 1998; Grullon et al., 2009).

4.5. Factiva

We use Factiva to investigate the media coverage of advisers and brokers that halt suspicious transactions. Factiva is a global news search engine produced by Dow Jones & Company. It provides access to more than 32,000 global media sources, including national, international, and regional newspapers, newswires, TV and radio podcasts, news and business information websites, blogs, message boards, and more.

4.6. U.S. Census Bureau

We use data on counties from the U.S. Census Bureau as control variables. These data include the number of persons of 65 years of age or older, gender makeup, ethnic composition, average retirement income, and total income.

[24]More details regarding the census can be found here: http://www.usreligioncensus.org/datacol.php.

4.7. Summary Statistics

Our sample includes monthly observations for 2,557 counties from April 2012 to July 2019, resulting in 225,016 total number of observations. Table 3 presents summary statistics for the counties in our sample over the sample period. The average number of reported senior financial exploitation cases in a county-month is 0.8, with a standard deviation of 2.7. Approximately 82% of counties have zero reported cases in a month. The 99th percentile of reported senior financial fraud in a county-month is 14.

In terms of access to financial professionals, the average number of investment advisers (brokers) per 1,000 individuals is 0.6 (1.1). Their per capita presence varies from 0 to 3.8 for advisers and 0 to 7.6 for brokers. There is a large distribution in access to financial professionals as the standard deviations of these variables are twice as large as the mean. Approximately, 80% of advisers are dual-registered as brokers, whereas about 50% of brokers are dual registered as advisers. These numbers have meaningful cross-sectional variation, demonstrated by a standard deviation of 60% and 30%, respectively.

In an average county, roughly 18% of the population is 65 years of age or older. This statistic varies substantially across states, ranging from around 11% in Utah to 22% in Florida. In our analysis, we control for this variation to adjust for the base of the senior population. In terms of economic conditions, the counties average $74,400 in household income, $22,348 in retirement income, and a credit score of 673. An average county has 42% subprime borrowers (credit score below 660) and an average debt-to-income ratio of approximately 12.

5. Results

5.1. Empirical Specification

We employ a generalized difference-in-differences approach. This approach exploits the staggered passage of regulations across states empowering financial professionals to halt suspicious disbursements of funds from the accounts of the elderly. More specifically, we exploit differences across states in the timing of passage of the Model Act (affecting both brokers and investment advisers) and the timing of FINRA's national rule change (affecting brokers). Table 2 details when states adopted the Model Act. As noted before, there was no concomitant change in the reporting requirements of suspicious transactions to the U.S. Treasury, and we are unaware of any other confounding events or rule changes that took place simultaneously with the adoption of these policies.

We estimate models of the following form:

$$OUTCOME_{ct} = \alpha + \beta POST_{st} + \gamma' \mathbf{X}_{ct} + \eta_c + \eta_t + \epsilon_{ct} \tag{1}$$

We index county by c, state by s, and month by t. $POST_{st}$ is an indicator variable that equals to one when any financial professional in a state is first permitted to halt suspicious transactions. Figure 1 Panel B shows variations in this date across states. The β on $POST_{st}$ measures the effect of the rule change.[25] $\mathbf{X}_{ct}$ denotes a vector of time-varying county demographic and economic characteristics, such as the number and average credit score of persons 65 years of age or older in a county. Our main specification includes a set of county fixed effects, denoted by η_c, to absorb any unobserved persistent county characteristics. We also include month fixed effects, denoted by η_t, to account for nationwide trends. We cluster standard errors at the county level.

The key identifying assumption underlying our empirical strategy is that states' timing of adoption is independent of factors that might otherwise affect elder financial abuse. We take a variety of measures to substantiate this assumption. First, Figure 2 shows, in event time, no unusual changes in elder financial exploitation prior to the rule change, and a noticeable drop only upon passage.

Second, for the 25 Model Act states, we find no relationship between the timing of adoption by individual states and a wide range of state economic and demographic characteristics, such as the preexisting level of elder abuse, the fraction of seniors in the population, average household income and credit scores, and the share of the population that is male or married. In Figure 3 and Appendix Table A1, we show both graphically and in regressions that none of these variables predict the timing of adoption. Moreover, because we rely on monthly variation in the timing of adoption within a relatively short time window (2-3 years), small differences in timing likely results from idiosyncratic conventions by state legislators to meet at different times to set the effective dates for new laws.

Figure 2 does show that the effect of the policy is not complete in the quarter of adoption. For staggered difference-in-differences designs, an incomplete response to the policy works against identifying a result, because when the "already treated" counties are used as a control group, the control group's elder abuse cases are trending in the same direction - that is still dropping (Goodman-Bacon, 2018). Its not surprising that the policy's effect is not complete immediately, as it takes time for advisers and brokers to learn about the legislation and develop protocols for implementation. Moreover, the deterrence effect of allowing financial professionals to halt transactions may take time to become known among the perpetrators.

[25]The staggered difference-in-difference approach uses three distinct sources of variations: the difference in treatment timing across the timing group, the timing group compared with the never-treated group, and the timing group compared with the always-treated group. See Appendix B for a decomposition of this effect by the source of variation, as outlined in Goodman-Bacon (2018).

5.2. Main Effects

We find that deputizing appears to be effective at deterring financial exploitation of the elderly. Table 4 panel A shows the results. The outcome variable is the natural logarithm of one plus the number of suspected elder financial exploitation cases in a county in a month.[26] Column (1) shows a 6.2% decrease in financial exploitation in treated states. Column (2) shows a 3.0% decrease when including county-level demographic and economic control variables. These controls increase the adjusted R^2 from 7% to 39%. In columns (3) and (4), we further control for a set of state fixed effects and county fixed effects, respectively, to account for geographic time-invariant characteristics.

The economic magnitudes in Panel A suggest an annual reduction of between 866 and 1,732 elder financial exploitation cases across the U.S.[27] Overall, the estimated decline in financial exploitation remains statistically significant at the 1% level and quantitatively similar across specifications.

Table 4 Panel B further presents the results in terms of the extensive margin. The outcome variable is an indicator variable that equals to one if a county has one or more cases of senior financial exploitation in a given month. The policy reduces the monthly probability of exploitation by 1.7-3.4 percentage points, depending on the specification. This effect represents about 10-20% of the unconditional probability of having at least one senior financial fraud case in a county-month, which is approximately 18%.

Admittedly, while we show parallel *pre*-treatment trends in Figure 2, the parallel trend assumption—that treated and control groups would have experienced parallel changes *post*-treatment—is inherently untestable. To investigate this further, we repeat a difference-in-differences specification with a subsample of counties that are matched on pre-treatment characteristics. Matching should ensure that counties achieve covariate balance on observed attributes and hopefully also brings them closer on unobserved dimensions to help reduce the risk of non-parallel trends.

We use the following minimum distance matching procedure: for each county, we calculate its geometric distance to all other counties based on a vector of covariates (the control variables in Table 4).[28] So that each covariate receives an equal weight, we standardize them

[26]While our outcome variable of interest is the number of suspected elder abuse cases, a Consumer Financial Protection Bureau report suggests that 80% of the suspected cases do involve a financial loss to the elderly. https://files.consumerfinance.gov/f/documents/cfpb_suspicious-activity-reports-elder-financial-exploitation_report.pdf

[27]A 3-6% reduction on an average of 0.8 cases per county-month is a reduction of 0.024-0.048 cases per county-month. Multiplying this value by 12 months a year and by 3,007 counties in the U.S. gives between 866 and 1,732 cases per year.

[28]Geometric distance is the square root of the sum of the squares of the differences in covariates between two counties. Mathematically, the geometric distance metric is d_{ij} =

to have a mean of zero and a standard deviation of one. Next, for each county, we select a pair-county that has the smallest geometric distance, is located in a different state, and receives treatment at a different point in time.

We perform the difference-in-difference regressions, including a set of matched-pair fixed effects to ensure that treatment effects are identified from within-pair comparisons. Table 5 Panel A shows that the estimates using matched county pairs are statistically significant and economically similar to those presented in Table 4. Table 5 Panels B-E report the covariate balance tables for each of the distance thresholds we employ, which show that paired counties are similar in observable aspects.

The drop in abuse that we have documented in both sets of tests is also robust to other specifications. In Appendix Figure A1, we show the main effect in Table 4 Panel A Column (4) is robust to dropping any state. Appendix Table A2 further shows a similar drop when the sample is cut off in January 2018, prior to enactment of FINRA 2165.

5.3. Who did the policy protect more?

Certain demographic and socioeconomic groups may be more vulnerable to financial exploitation, such as women, minorities, and less-educated people (e.g. Lusardi and Mitchell, 2011; Lusardi et al., 2018a,b). To this end, we gather variables that measure the demographic composition of seniors in a county, such as gender, race, educational attainment, and marital status, and their corresponding economic characteristics such as income and credit score. We interact $Post_{st}$ with indicator variables that take a value of one if the variable is above the national median as of December 2015, the month prior to the finalization of Model Act.

Table 6 presents the results. Columns (1) through (2) show that the policy was primarily effective in counties with higher income levels and higher retirement incomes. Column (3) suggests that the effect may also be stronger in counties with higher average credit scores. There are two possible explanations for this result. First, individuals with higher wealth have better access to financial professionals that can now protect them. Second, it is possible that people with higher wealth are more attractive targets for exploitation. In the elderly population, where all people are susceptible to decline, wealth is not necessarily a proxy for financial literacy.

Table 6 Columns (4) and (5) show that the effect of the policy is greater for elderly who are not married and are female. Indeed, widows and single elderly people should be more vulnerable to exploitation ex ante. In Column (6), we find no evidence that the effect is stronger in areas in which a higher fraction of the elderly are 85 years of age and above.

$\sqrt{(x_{1i}-x_{1j})^2+(x_{2i}-x_{2j})^2+...+(x_{Ni}-x_{Nj})^2}$, where x_1, x_2, ..., x_N are standardized covariates, and i and j denote counties.

In Column (7), the effect is larger in counties in which a higher proportion of adults have a bachelor's degree or higher. Columns (8) through (11) show that the policy benefits minorities to a greater extent, who may be less able to protect themselves from financial exploitation.

5.4. Welfare Implications

We next investigate the welfare implications of deputizing financial professionals by assessing the effect of the rule changes on personal bankruptcies by elderly people. Consumer bankruptcy is well-known to result in substantial damages to individuals and is a dead-weight loss to society (e.g. Athreya, 2002; Chatterjee and Gordon, 2012).

For this test, we use individual-level credit information from Experian for a random sample of 1% of individuals 65 years of age or older. We keep individuals in the sample once they reach the age of 65. We then follow these elderly individuals through time; our data spans 2010 to 2019. For each individual, we have annual credit information and the county of residence.

Table 7 presents the results. The outcome variable is an indicator that equals 100 if the individual experienced a bankruptcy in a given year. *Post* is the fraction of the year that the policy was in effect in the state the individual lives that year. Column (1) includes *Post* as well as county and year fixed effects. Column (2) adds controls for an individual's credit score, age, estimated household income, marriage status, and gender. Column (3) adds person fixed effects. The estimated effect on bankruptcies is negative and economically meaningful across these specifications. According to Column (3), the rule change reduced the probability of bankruptcy by 0.12 percentage points, which is about 4.5% of the unconditional probability of bankruptcy of 2.75%.

6. Mechanisms

Our results so far suggest that the newly-passed elderly protection laws were effective at deterring abuse, even without an explicit incentive provision. The success of the laws, therefore, had to rely on existing mechanisms such as reputational concerns, preserving fees from AUM, moral imperatives, ethical codes, social awareness, or relationships. In this section, we explore these various possible mechanisms to explain why deputization appeared to work.

6.1. Law as Public Signal

Sunstein (1996) and McAdams (1997) suggest that laws signal societal values to a community, express generally-held beliefs about what is right and wrong, and shape desirable social norms. Hence, the values the laws express can induce compliance, independently from the sanctions the laws threaten or the rewards the laws provide. For example, laws that require clean-up after one's pet can strengthen the norm of cleaning up, even in the absence of enforcement. Laws banning smoking signal to smokers a societal consensus that exposing others to smoke is offensive, triggering smokers to refrain from smoking in public places.

Following a similar line of thinking, we might expect that the laws we study in this paper signal or strengthen a negative societal perception of elder abuse, motivating financial professionals to serve as protectors. This hypothesis would suggest that *both* investment advisers and brokers should engage in halting suspicious transactions and preventing abuse, given that they would be equally exposed to the law-induced change in the perception of abuse.

To test this hypothesis, in Table 8, we analyze whether both advisers and brokers respond to the new laws and help decrease elder abuse. We calculate the per capita number of brokers and investment advisers operating at branches in every county each month. We then define indicator variables that equal one if a county's per capita number of brokers or advisers exceeds the national median. Unsurprisingly, the coefficients in Columns (1) and (2) suggest that the laws reduce financial exploitation primarily in counties with above-median per capita advisers and brokers.

However, Column (3) shows that the reduction in financial exploitation occurs only in counties with above-median advisers per capita rather than above-median brokers per capita. Specifically, after conditioning on the presence of advisers in a county, the policy does not generate a statistically different effect in counties with high and low presence of brokers. Relatedly, Column (4) shows that the effect is weaker when a higher fraction of advisers in a county are dual-registered as brokers. Such advisers may have a more transactional relationship with clients than pure advisers. This dichotomy suggests that the advisers, not the brokers, respond to the policy change. The distinction appears to be inconsistent with a signaling role of the new regulations.

An alternative signaling story could be that adoption of the new laws signals increased regulatory concern with elder financial exploitation and thus increased oversight and monitoring of advisers and brokers. Again, the differential effects on advisers and brokers seem inconsistent with this argument. We also examine monitoring more directly in Table 9 by gathering all of the disclosures individual advisers and brokers must make. In Column (1), we do not observe a statistically significant increase in disclosures of regulatory actions taken against advisers and brokers. If regulators became more active, we would have expected an increase in regulatory actions. In Columns (2) and (3), we do not find evidence that misconduct by advisers and brokers decreases. More specifically, there is no drop in criminal activities or activities that result in customer complaints. We would have expected a reduction in misconduct if regulatory scrutiny increased.[29]

6.2. Ethical Code vs Social Awareness

The success of deputization could depend on the deputies' intrinsic incentives to do the right thing for others. Many thought leaders in economics have suggested that agents often conform to ethical codes rather than act egoistically (e.g. Arrow, 1988; Brennan, 1994; Akerlof, 2007).[30] Potentially, these intrinsic motivations could stem from moral beliefs, relationships in the local community, or both.

To explore this, we examine whether the laws are more effective in areas with higher religious adherents per capita and in areas with higher religious congregations per capita. Religion has been argued to promote ethical behavior.[31] In contrast, conditional on the overall religiosity of a particular area, a larger number of congregations might suggest that the community is more socially fractured and less well-connected.

Our data on a county's number of religious adherents and congregations come from the 2010 U.S. Religion Census conducted by the ASARB. A congregation is generally defined as a group of people who meet regularly (typically weekly or monthly) at a preannounced time and location. Congregations may be churches, mosques, temples, or other meeting places. Adherents include all people with an affiliation to a congregation (children, members, and attendees who are not members).

In Table 10, the coefficient estimates in Column (1) suggest that the laws have a similar effect in counties with an above- and below-median number of religious adherents per capita. However, Columns (2) and (3) show that the effect of the law is significantly weaker in counties with an above-median number of congregations per capita, even conditional on adherents (Column (3)). These results provide support for a mechanism based on relationships with clients and the community, rather than a mechanism based on moral imperatives.

[29] Due to data limitations, we conduct Table 9 tests on the subsample of advisers that are dual-registered as brokers, which comprise 80% of the entire universe of advisers. This sample restriction should bias our results towards finding supportive evidence for the monitoring hypothesis, because Charoenwong et al. (2019) shows that the behavior of brokers are more sensitive to changes in regulatory oversight than the behavior of advisers.

[30] As far back as Aristotle (in Nicomachean Ethics), it was proposed that individuals in a civilized society incorporate ethical standards into the decisions that they make (Aristotle, 2004). This has been studied in psychology (Judge and Ilies, 2002), law (Shavell, 2002), politics (Kaplow and Shavell, 2007), economics (Frank, 1987; Noe and Rebello, 1994), and finance (Carlin and Gervais, 2009). See Carlin et al. (2009) and Sapienza et al. (2013) for an analysis of trust formation in markets.

[31] Adam Smith emphasized the influence of religious morality in engendering feelings of guilt or pride as a motivator of proper behavior (Smith, 2010). Though still a question of continuing interest and debate, there is empirical evidence supporting the role of religion in deterring unethical behaviors in economics and finance. For example, see Guiso et al. (2003) and Grullon et al. (2009).

The relationship mechanism may be important for a few reasons. First, more connected communities involve stronger personal relationships that may help financial professionals identify unusual activity. Second, professionals in such communities and relationships are more likely to derive utility from the increases in welfare of others (Leider et al., 2009). Third, social norms and morality may only be applicable to a narrow community, such as a congregation (Tabellini, 2008). Fourth, stronger communities entail more reciprocal exchange, creating incentives to protect clients from abuse (Kranton, 1996).

There are a two additional results that support a relationship mechanism. First, the fact that the policy works through advisers rather than brokers is consistent with a relationship mechanism (Table 8). More specifically, brokers likely have more arm's length and transactional relationships with clients. By contrast, advisers likely have stronger personal relationships with clients as a result of regular financial planning sessions that document clients' circumstances and objectives. Moreover, because regulators hold advisers to a fiduciary standard, which requires advisers to put a client's interests first, advisers likely develop deeper and more intimate relationships with clients.[32] By contrast, brokers likely develop a weaker sense of duty to clients as regulators hold brokers to a weaker suitability standard, which allows brokers to put their interests before their clients' interests.

A second piece of evidence consistent with the relationship mechanism is that the policy primarily operates through advisers that are more rooted in a community. Our individual-level panel dataset of advisers allows us to measure how many months each adviser has worked in a certain county. We define an indicator variable *High Time in County* that equals one when the average time advisers have been in a county exceeds the national median. Table 11 Panel A Column (1) shows that the decline in financial exploitation of the elderly is about 6% in counties with more rooted advisers who have been in the county longer and only 2% in counties with less rooted advisers. Relatedly, in Column (4), we also show the decline is weaker in counties in which the average adviser is registered to operate in more states. When advisers register in more states, their clients are likely more dispersed.

A possible alternative explanation is that advisers who have spent longer in the county have also spent more time in the profession and are more experienced. More experienced finance professionals may be better able to spot financial exploitation. Columns (2) and (5) rule out this hypothesis and shows that time in the county is what matters, not time in the profession. Also, more time in the county could proxy for more time at a firm, which may correlate with the quality of the adviser and the adviser's familiarity with the firm's systems. However, columns (3) and (5) also rule out this alternative.

[32] See https://www.sec.gov/rules/interp/2019/ia-5248.pdf.

6.3. Egoistic Incentives

Certainly, most economic thought is founded on the principle that agents are egoistic and must be given incentives to act.[33] In this setting, advisers might have served as deputies for their own monetary gain, which may include incentives to preserve fees that they earn from managing assets or by getting publicizing themselves as protectors of the community.

At the level of a single client, the amount of business (AUM) that would be protected when a fiduciary acts as a deputy is small relative to the costs of doing so. Before investigating this formally, consider the following back-of-the-envelope calculation. In our sample, the average assets under management for an individual is $30,000. Even if all of the capital were at risk, and the adviser were to earn 1% per year for their services, deputization would preserve $300 per year. Compared to the time cost of dealing with regulators and the implementation of monitoring systems required by law, halting transactions is unlikely to be lucrative.

We explore the egoism mechanism more formally in a number of ways. First, we test whether the decline in exploitation is larger in counties with more misbehaving financial professionals. Misbehaving professionals may prioritize fees over client well-being. We measure misconduct by counting the ex-ante number of disclosures a financial professional makes on her Form U4 filing. Disclosures include customer complaints, regulatory actions, civil and criminal events, and terminations. Table 8 Column (5) shows that the decline in abuse is unrelated to whether financial professionals in a county misbehave more than the national median.

Second, in Table 12, we examine how the policy's effect relates to the type of fees firms charge clients. This data comes from the Form ADV filed annually by each registered investment adviser firm with the SEC. For each county, we match all individual advisers with their firm's characteristics and then take an average, so that a county's measures are weighted by the number of individual advisers operating in that county.

If revenue preservation explains the incentive to be a deputy, the effect of the policy should be stronger when advisers have a more valuable fee stream to protect. This would be higher with a recurring fee stream from AUM than with one-off services that are billed hourly. Column (1) of Table 12, however, shows that the effect is unrelated to the degree to which advisers charge clients a percentage of AUM. Also, Column (2) shows that the policy's effect does not relate with the extent to which advisers charge hourly fees. Column (3) shows the effect is unrelated to whether firms charge clients commissions, which tend to be charged

[33] Key papers that formally develop this idea in the theory of agency include Ross (1973), Jensen and Meckling (1976), Harris and Raviv (1979), and Hölmstrom (1979).

by advisery firms dual-registered as broker-dealers. Overall, there is little evidence that the type of compensation arrangements advisers have with clients relates to the policy's effect.

Finally, deputies could also have egoistic incentives that stem from publicizing their reputation. If, through halting suspicious transactions, advisers and brokers earn the reputation of protecting clients, then they could leverage the new regulation to expand their client base. This alternative mechanism would be plausible if there are systematic ways for advisers and brokers to "market" the delay of transactions to the general public. However, neither the Investment Adviser Public Disclosure (IAPD) website nor FINRA's BrokerCheck website disclose such information regarding brokers and advisers.

To investigate this further, we searched Factiva's news database to analyze the frequency with which the local and national media cover an adviser's or broker's efforts to protect elders from financial exploitation. If this channel were important, we would expect to find many articles that publicized either individual heroism for protecting people or poor press for allowing clients to be injured.

We searched for articles that include the following set of words: "adviser" or "advisor", "halt" or "delay", and "financial abuse" or "financial exploitation." We find only 67 such articles released during 2015 to 2020 across the United States. This frequency is equivalent to an average of 0.3 articles per state per year. Inspection of these articles reveals that none specifically mention a particular adviser or broker by name, but rather only include general discussions of the problem of elder financial exploitation or the new regulation. As such, publicizing reputation through the media does not appear to be a way in which individual advisers or brokers manage their reputations about the extent to which they protect elders from financial exploitation.[34]

7. Conclusion

Before implementing the new rules, it was unclear whether empowering financial professionals to be monitors would be effective in curbing senior financial exploitation, without providing explicit incentives. The new rules did not include penalties for not participating or monetary incentives for catching abusers, but instead relied on existing social or market mechanisms.

Our results suggest that deputization was successful in reducing the abuse of seniors, especially for those who are most at risk. The channels that appeared to be responsible were social awareness, community connectedness, and deeper personal relationships. Egoistic

[34] We use various other combinations of texts to identify articles. We present the detailed texts, dates, regions, and timestamps of the searches in the Appendix Table A4.

incentives to preserve commissions, legal motivations, and publicity appeared to be less important.

Overall, our findings give hope for the use of deputization in the future in other venues. If it works in the finance industry, we are sanguine about its success in more altruistic settings.

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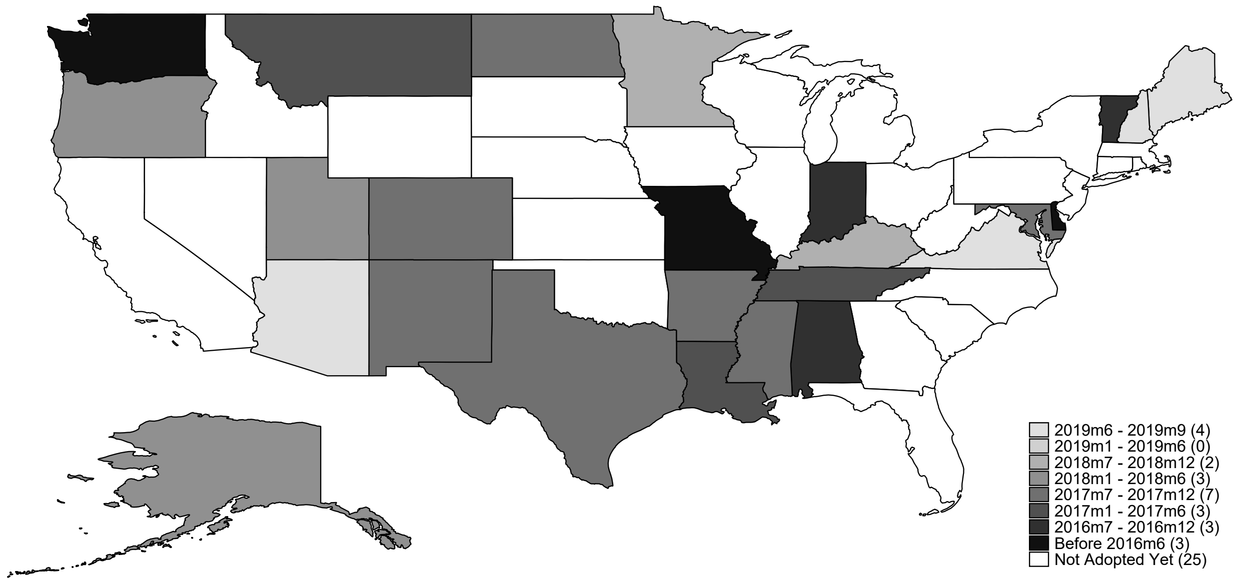
Figure 1: Staggered Adoption

Panel A shows the staggered adoption of the Model Act or similar provisions across states. In Panel B, we plot the date after which financial professionals are first empowered to halt suspicious transactions, either because a state adopts the Model Act or FINRA passes Rule 2165.

Panel A: Model Act Adoption Date



Panel B: First Adoption Date: Model Act or FINRA Rule 2165

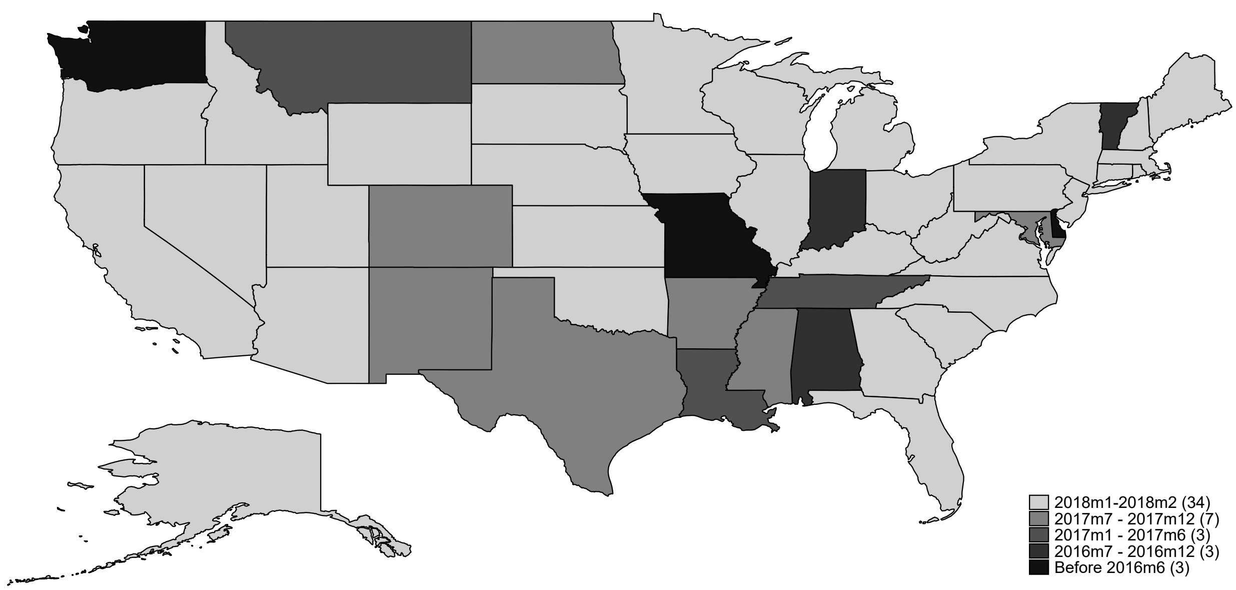


Figure 2: Annual Difference-in-Difference Coefficient Plot

This figure shows the annual difference-in-difference coefficient estimates and 95% confidence intervals based on standard errors clustered at the county level. The red vertical line indicates the month of treatment. The outcome variable is *Ln(1+Elder Financial Exploitation Cases)*, the natural logarithm of one plus the number of elder financial exploitation cases in a county-month.

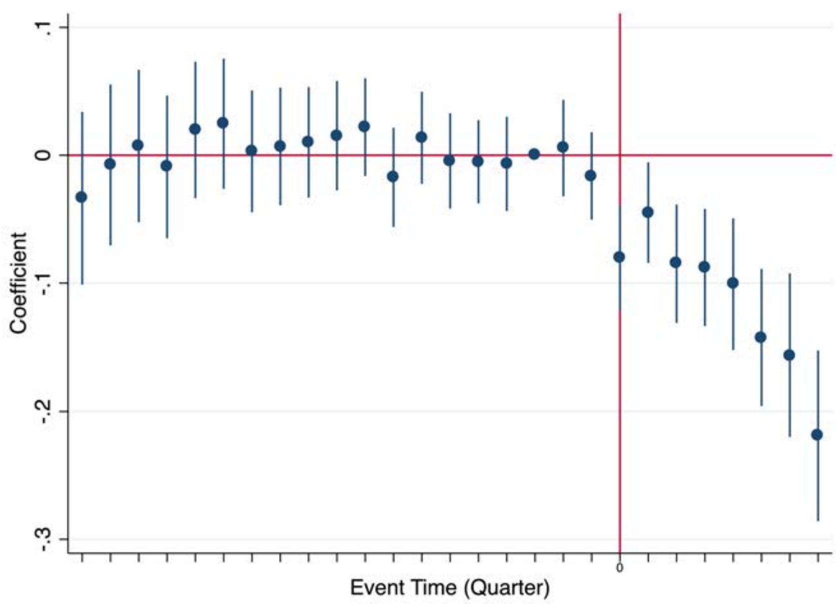


Figure 3: Do state characteristics predict the timing of adoption?

Figure 3 shows the scatter plots of the timing of the policy adoption against state characteristics for the 24 states that adopted the senior protection legislation in a staggered manner during our sample period (April 2012 - September 2019). The corresponding regression results are reported in the Appendix Table A1. The variable plotted on the y-axis, *Group of Adoption*, is equal to 1 for the earliest adopting state, 2 for the second earliest adopting state, and so on. State labels are displayed next to each data point. The coefficients and p-values of the slopes are reported at the top-right corner of each figure. *Number of Elder Exploitation Cases Per 1000* measures the number of elder exploitation cases per 1,000 population that are age 65 and above. *Frac Pop Abovve 65* measures the fraction of population that are age 65 and above. *Average Household Income (Credit Score)* measures the average household income (credit score) in a state. *Fraction of Married (Male)* measures the fraction of population in a state that is married (male). All variables on the x-axis are measured as of 2015, the year before the Model Act was finalized.

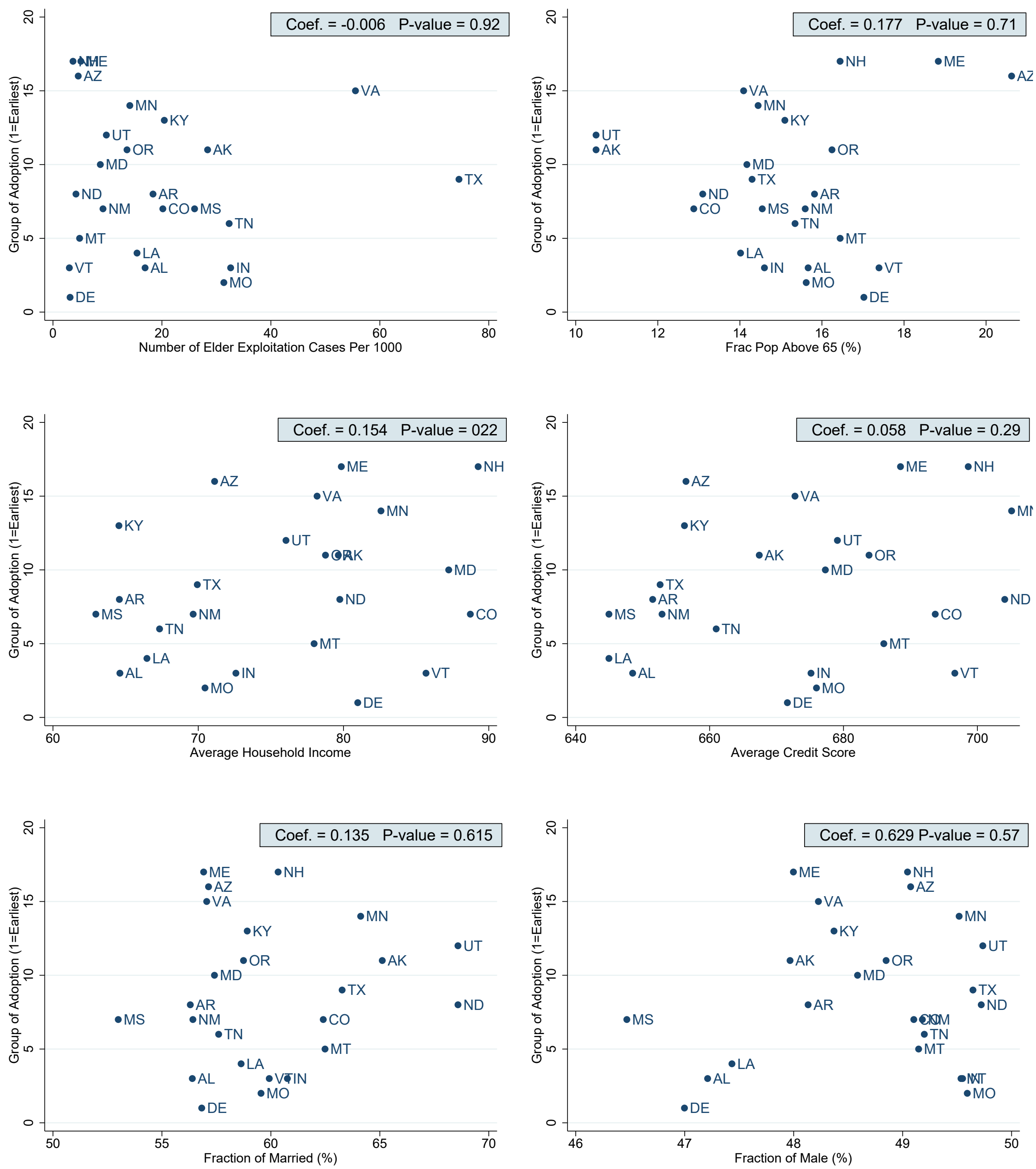


Table 1: Comparison Between NASAA Model Act and FINRA Rule 2165

This table presents a detailed comparison between the institutional features of the NASAA Model Act and FINRA Rule 2165, along dimensions such as adoption status, applicable institutions, adults covered, temporary holds, the granting of immunity, reporting requirement to APS, record sharing, and training. A more detailed discussion can be found in Section 3.

	NASAA Model Act	**FINRA Rule 2165**
Adoption status	Staggered adoption by state	Nationwide adoption on Feb 5, 2018
Applies to Whom	Agents, broker-dealers, and investment advisers	FINRA-registered broker-dealers
Adults Covered	A person 65 years of age or older or a person subject to a state APS statute	A person age 65 and older or a person age 18 and older with mental or physical impairment
Holds Applicability	Disbursements of funds	Disbursements of funds or securities
Holds Period	The sooner of (a) a determination that the disbursement will not result in financial exploitation of the eligible adult; or (b) 15 business days after the date on which disbursement of the funds was delayed, unless APS or the Commissioner of Securities requests an extension of the delay, in which it shall expire no more than 25 business days after the date on which the disbursement was first delayed.	15 business days unless (1) otherwise terminated or extended by a state regulator, or agency of competent jurisdiction, or a court of competent jurisdiction; or (2) extended by the member firm for no longer than 10 business days.
Immunity	Agents, Broker-Dealers, and Investment Advisers	N/A
Reporting to APS	Mandatory	Voluntary
Record Sharing	Mandatory with APS and law enforcement	Mandatory upon FINRA request
Training	N/A	Pursuant to Supplementary Material .02 (Training), a FINRA member firm relying on Rule 2165 must develop and document training policies or programs reasonably designed to ensure that associated persons comply with the requirements of Rule 2165.

Table 2: Staggered Adoption of NASAA Model Act

This table shows the staggered adoption of NASAA Model Act across U.S. states from 2010 to 2019. We identify state-level acts, laws, statutes, and regulations that are based on the Model Act or contain similar provisions to those in the Model Act. For each state, we obtain the the passage date, the effective date, and the applicable institutions from state's legislature website. States with a * next to them are states that adopted provisions similar to those in the Model Act before the Model Act was proposed.

State	**Passage Date**	**Effective Date**	**Applies to Whom**
AL	4/15/2016	7/1/2016	Broker-dealers and investment advisers
AK	4/17/2017	1/1/2018	Broker-dealers and investment advisers
AZ	5/13/2019	8/27/2019	Broker-dealers and investment advisers
AR	3/27/2017	8/7/2017	Broker-dealers and investment advisers
CO	6/2/2017	7/1/2017	Broker-dealers and investment advisers
DE*	9/30/2014	9/30/2014	Financial Institutions
DE	8/29/2018	11/27/2018	Broker-dealers and investment advisers
IN	3/21/2016	7/1/2016	Broker-dealers
IN	4/24/2017	7/1/2017	Investment advisers
KY	4/10/2018	7/14/2018	Financial institutions (Including broker-dealers and investment advisers)
LA	6/17/2016	1/1/2017	Broker-dealers and investment advisers
ME	4/2/2019	9/19/2019	Broker-dealers and investment advisers
MD	5/27/2017	10/1/2017	Broker-dealers and investment advisers
MN	5/19/2018	8/1/2018	Broker-dealers and investment advisers
MO*	6/12/2015	8/28/2015	Broker-dealers
MS	3/27/2017	7/1/2017	Broker-dealers and investment advisers
MT	3/22/2017	3/22/2017	Broker-dealers and investment advisers
NH	7/10/2019	9/8/2019	Broker-dealers and investment advisers
NM	4/6/2017	7/1/2017	Broker-dealers and investment advisers
ND	4/10/2017	8/1/2017	Broker-dealers and investment advisers
OR	6/29/2017	1/1/2018	Broker-dealers and investment advisers
TN	5/18/2017	5/18/2017	Broker-dealers and investment advisers
TX	6/1/2017	9/1/2017	Financial institutions (Including broker-dealers and investment advisers)
UT	3/16/2018	5/8/2018	Broker-dealers and investment advisers
VT		7/1/2016	Broker-dealers and investment advisers
VA	3/18/2019	7/1/2019	Financial institutions (Including broker-dealers and investment advisers)
WA*	3/19/2010	6/10/2010	Financial institutions (Including broker-dealers and investment advisers)

Table 3: Summary Statistics

This table reports county-level summary statistics for variables related to elder financial exploitation, the presence of investment advisers and brokers, and demographic and economic characteristics. The unit of observation is a county-month. The sample includes all counties that have at least one elder financial exploitation case reported to the Department of Treasury from April 2012 to September 2019. *Elder Financial Exploitation Cases* is the county-month count of transactions that are suspected to result in the financial exploitation of an elderly person and are reported to the Department of Treasury. *Elder Financial Exploitation Probability* is an indicator variable that equals to one if a county-month count of elder financial exploitation cases is above zero. *Advisers Per 1,000* is the number of investment advisers in a county divided by the total number of persons that are 16 years of age or older, multiplied by 1,000. *Brokers Per 1,000* is the number of broker-dealers in a county divided by the total number of persons that are 16 years of age or older, multiplied by 1,000. *Fraction of Dual-Registered Advisers (Brokers)* is the fraction of advisers (brokers) in a county that are dual-registered as brokers (advisers). *Population Above 65* is the number of persons above the age of 65. *Fraction of Population Above 65* is the number of persons above the age of 65 divided by the total population. *Vantage Score* is the average credit score in a county-month based on a 1% representative sample of credit bureau records. *Fraction of Subprime* is the fraction of residents with a credit score below 660. *Fraction of Low Income* is the fraction of residents with income below the national median. *Average Age* is the average age of all residents in a county. *Fraction of Male* is the fraction of male residents. *Fraction of Married* is the fraction of married residents. *Household Income* is the average household income in a county. *Household Debt-to-Income Ratio* is the average household debt-to-income ratio in a county. *Average Retirement Income* is the average personal retirement income for retirees.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Mean	SD	p10	p50	p90	N
Elder Financial Exploitation Cases	0.8	2.7	0.0	0.0	2.0	225,016
Elder Financial Exploitation Probability	0.2	0.4	0.0	0.0	1.0	225,016
Advisers Per 1,000	0.6	1.0	0.0	0.3	1.3	225,016
Brokers Per 1,000	1.1	2.1	0.1	0.7	2.2	225,016
Fraction of Dual-Registered Advisers	0.8	0.6	0.0	0.9	1.0	225,016
Fraction of Dual-Registered Brokers	0.5	0.3	0.2	0.5	0.7	211,355
Population Above 65	18,516.7	48,185.0	1,805	6,226	39,617	225,016
Fraction of Population Above 65	0.2	0.0	0.1	0.2	0.2	207,117
Vantage Score	673.2	26.1	638.7	674.0	707.2	225,016
Fraction of Subprime	0.4	0.1	0.3	0.4	0.6	225,016
Fraction of Low Income	0.5	0.1	0.4	0.5	0.7	225,016
Average Age	52.8	2.9	49.1	52.8	56.6	225,016
Fraction of Male	0.5	0.0	0.4	0.5	0.5	225,016
Fraction of Married	0.6	0.1	0.5	0.6	0.7	225,016
Household Income	74.4	12.4	60.3	72.7	90.4	225,016
Household Debt-to-Income Ratio	11.9	1.8	9.6	11.8	14.3	225,016
Average Retirement Income	22,347.8	5,280.8	16,566	21,402	29,264	225,016
Religious Adherent Per 1000	501.1	167.0	301.5	485.6	713.9	225,016
Religious Congregation Per 1000	2.1	1.1	0.8	1.9	3.5	225,016

Table 4: Effects of Deputization on Elder Financial Exploitation

This table presents difference-in-differences estimates of the effect of the deputizing financial professionals on elder financial exploitation. The sample includes monthly observations for 2,557 counties from April 2012 to September 2019. In Panel A, the outcome variable is the natural logarithm of one plus the number of elder financial exploitation cases in a county-month. In Panel B, the outcome variable is an indicator variable that equals to one if a county-month has above zero elder financial exploitation cases. *Post* is an indicator variable that equals to one after financial professionals are first empowered to halt suspicious transactions, either because a state adopts the Model Act or FINRA passes Rule 2165. A detailed description of the control variables can be found in Table 3's legend. Standard errors, adjusted for clustering at the county level, are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively

Panel A: Ln(1+Elder Financial Exploitation Cases)				
	(1)	(2)	(3)	(4)
Post	-0.062**	-0.030**	-0.043***	-0.038***
	(0.025)	(0.014)	(0.009)	(0.009)
Log Pop Above 65		0.270***	0.279***	1.112***
		(0.008)	(0.008)	(0.193)
Vantage Score		-0.059***	-0.036**	0.077***
		(0.014)	(0.015)	(0.016)
Fraction of Subprime		0.006	0.009	-0.026***
		(0.013)	(0.012)	(0.010)
Fraction of Low Income		0.050***	0.041***	0.022***
		(0.009)	(0.008)	(0.006)
Average Age		-0.013**	-0.011**	-0.085***
		(0.005)	(0.005)	(0.009)
Fraction of Male		0.005	0.000	0.006*
		(0.003)	(0.003)	(0.004)
Fraction of Married		0.011**	0.001	0.012***
		(0.005)	(0.005)	(0.004)
Household Income		0.091***	0.055***	0.039**
		(0.011)	(0.012)	(0.016)
Household Debt-to-Income Ratio		-0.026***	-0.032***	-0.001
		(0.005)	(0.005)	(0.005)
Fraction with Bachelor or Higher		0.174***	0.174***	0.196***
		(0.010)	(0.010)	(0.010)
Constant	0.270***	0.261***	0.265***	0.263***
	(0.010)	(0.005)	(0.005)	(0.002)
Year-Month FE	Yes	Yes	Yes	Yes
State FE	No	No	Yes	No
County FE	No	No	No	Yes
Adjusted R^2	0.07	0.39	0.40	0.50
# Counties	2557	2557	2557	2557
Observations	225016	225016	225016	225016

Panel B: I(Elder Financial Exploitation Cases)>0				
	(1)	(2)	(3)	(4)
Post	-0.034**	-0.019***	-0.019***	-0.016***
	(0.013)	(0.006)	(0.005)	(0.005)
Log Pop Above 65		0.160***	0.166***	0.905***
		(0.003)	(0.003)	(0.074)
Vantage Score		-0.029***	-0.014*	0.021***
		(0.008)	(0.008)	(0.008)
Fraction of Subprime		-0.000	0.001	-0.006
		(0.007)	(0.007)	(0.005)
Fraction of Low Income		0.018***	0.014***	0.008**
		(0.004)	(0.004)	(0.003)
Average Age		-0.005**	-0.004*	-0.023***
		(0.002)	(0.002)	(0.004)
Fraction of Male		0.001	-0.001	0.002
		(0.002)	(0.002)	(0.002)
Fraction of Married		0.003	-0.000	0.008***
		(0.002)	(0.002)	(0.002)
Household Income		0.038***	0.018***	-0.011*
		(0.005)	(0.005)	(0.007)
Household Debt-to-Income Ratio		-0.005**	-0.007***	-0.001
		(0.002)	(0.002)	(0.002)
Fraction with Bachelor or Higher		0.079***	0.079***	0.079***
		(0.004)	(0.004)	(0.004)
Constant	0.187***	0.183***	0.183***	0.182***
	(0.006)	(0.002)	(0.002)	(0.001)
Year-Month FE	Yes	Yes	Yes	Yes
State FE	No	No	Yes	No
County FE	No	No	No	Yes
Adjusted R^2	0.07	0.32	0.33	0.37
# Counties	2557	2557	2557	2557
Observations	225016	225016	225016	225016

Table 5: Effects of Deputization on a Matched Sample of Counties

In this table, we perform the difference-in-difference analysis in Table 4 on a subsample of matched counties by including fixed effects for each matched-pair. We use the following minimum distance matching procedure: for each county, we calculate its geometric distance to all other counties based on a vector of covariates. The covariates include the natural logarithm of population 65 years of age or older, average credit score, fraction of subprime borrowers, fraction of low income individuals, average age, fraction of male individuals, fraction of married individuals, household income, household debt-to-income ratios, and fraction with bachelor or higher. Geometric distance is calculated as the square root of the sum of the squares of the differences in covariates between two counties. Mathematically, it is expressed as $d_{ij} = \sqrt{(x_{1i} - x_{1j})^2 + (x_{2i} - x_{2j})^2 + ... + (x_{Ni} - x_{Nj})^2}$, where x_1, x_2, ..., x_N are standardized covariates, and i and j denote counties. All covariates are standardized to have a mean of zero and a standard deviation of one to receive equal weights. Next, for each county, we select a pair county that has the smallest geometric distance to the county, locates in a different state, and receives the treatment at a different point in time. Then, to ensure we use only high-quality matches, we keep the county pairs that have a geometric distance below a certain threshold. We use the 10^{th}, 25^{th}, 50^{th}, and 75^{th} percentiles of the distance distribution as different thresholds and our estimates of the effect are largely similar. Last, we use the subsamples of matched county pairs to perform difference-in-difference regressions, while including a set of matched-pair fixed effects. We present the regression results using different thresholds in Panel A. We also present the covariate balance tests on the matched sample of counties in Panels B-E, where *Treat* is an indicator variable that equals to one if a county is the early-adopter within a pair. *Post* is an indicator variable that equals to one after financial professionals are first empowered to halt suspicious transactions, either because a state adopts the Model Act or FINRA passes Rule 2165. Definitions of the control variables can be found in the Table 3 legend. Standard errors, adjusted for clustering at the county level, are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively

Panel A: Regression Results

	Ln(1+Elder Financial Exploitation Cases)			
	(1)	(2)	(3)	(4)
Geometric Distance Threshold:	10^{th} Percentile	25^{th} Percentile	50^{th} Percentile	75^{th} Percentile
Post	-0.047**	-0.038**	-0.026*	-0.031**
	(0.021)	(0.015)	(0.013)	(0.013)
Log Pop Above 65	1.197*	1.743***	2.181***	1.877***
	(0.617)	(0.351)	(0.278)	(0.244)
Vantage Score	0.106*	0.071*	0.059**	0.070***
	(0.057)	(0.038)	(0.028)	(0.023)
Fraction of Subprime	0.034	-0.005	-0.014	-0.009
	(0.041)	(0.026)	(0.019)	(0.015)
Fraction of Low Income	0.008	0.007	0.016	0.021**
	(0.027)	(0.017)	(0.012)	(0.010)
Average Age	-0.144***	-0.113***	-0.090***	-0.090***
	(0.036)	(0.024)	(0.016)	(0.013)
Fraction of Male	0.008	0.005	0.006	0.005
	(0.016)	(0.010)	(0.007)	(0.005)
Fraction of Married	-0.007	0.004	0.002	0.010
	(0.018)	(0.012)	(0.009)	(0.007)
Household Income	0.145**	0.098**	0.075***	0.068***
	(0.069)	(0.042)	(0.029)	(0.023)
Household Debt-to-Income Ratio	-0.006	-0.020*	-0.014*	-0.013**
	(0.017)	(0.011)	(0.008)	(0.006)
Fraction with Bachelor or Higher	0.324***	0.270***	0.241***	0.230***
	(0.034)	(0.024)	(0.017)	(0.015)
Constant	-0.016	-0.121	-0.160***	0.043
	(0.207)	(0.098)	(0.061)	(0.034)
Pair FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.37	0.39	0.43	0.45
# Counties	255	639	1279	1918
Observations	44880	112464	225104	337568

Panel B: Covariate Balance: 10th Percentile Threshold

	Treat = 0		Treat = 1			
	Mean	SD	Mean	SD	P-value	Std. Diff.
Elder Financial Exploitation Cases	0.40	(0.57)	0.34	(0.49)	(0.20)	-0.08
Log Population Above 65	0.31	(0.68)	0.32	(0.69)	(0.85)	0.01
Vantage Score	-0.43	(0.65)	-0.43	(0.63)	(0.98)	-0.00
Fraction of Subprime	0.40	(0.67)	0.39	(0.63)	(0.83)	-0.01
Fraction of Low Income	0.41	(0.74)	0.41	(0.72)	(0.99)	-0.00
Average Age	-0.16	(0.53)	-0.17	(0.53)	(0.84)	-0.01
Fraction of Male	-0.07	(0.49)	-0.07	(0.50)	(0.97)	0.00
Fraction of Married	-0.08	(0.63)	-0.08	(0.60)	(0.97)	-0.00
Household Income	-0.40	(0.59)	-0.41	(0.58)	(0.89)	-0.01
Household Debt-to-Income Ratio	0.05	(0.65)	0.05	(0.65)	(0.99)	0.00
Fraction with Bachelor or Higher	0.33	(0.56)	0.32	(0.56)	(0.78)	-0.02
Observations	255		255			

Panel C: Covariate Balance: 25th Percentile Threshold

	Treat = 0		Treat = 1			
	Mean	SD	Mean	SD	P-value	Std. Diff.
Log Population Above 65	0.26	(0.71)	0.26	(0.73)	(0.97)	0.00
Vantage Score	-0.35	(0.71)	-0.35	(0.70)	(0.94)	0.00
Fraction of Subprime	0.32	(0.72)	0.32	(0.69)	(0.92)	-0.00
Fraction of Low Income	0.37	(0.77)	0.36	(0.77)	(0.87)	-0.01
Average Age	-0.07	(0.62)	-0.09	(0.61)	(0.47)	-0.03
Fraction of Male	-0.02	(0.62)	-0.01	(0.61)	(0.87)	0.01
Fraction of Married	-0.07	(0.67)	-0.07	(0.66)	(1.00)	-0.00
Household Income	-0.34	(0.67)	-0.33	(0.65)	(0.89)	0.01
Household Debt-to-Income Ratio	-0.01	(0.66)	0.02	(0.66)	(0.44)	0.03
Fraction with Bachelor or Higher	0.36	(0.64)	0.35	(0.66)	(0.87)	-0.01
Observations	639		639			

Panel D: Covariate Balance: 50th Percentile Threshold

	Treat = 0		Treat = 1			
	Mean	SD	Mean	SD	P-value	Std. Diff.
Log Population Above 65	0.20	(0.78)	0.21	(0.77)	(0.83)	0.01
Vantage Score	-0.25	(0.81)	-0.27	(0.79)	(0.53)	-0.02
Fraction of Subprime	0.23	(0.81)	0.24	(0.78)	(0.77)	0.01
Fraction of Low Income	0.28	(0.84)	0.28	(0.83)	(0.95)	-0.00
Average Age	-0.07	(0.69)	-0.10	(0.69)	(0.25)	-0.03
Fraction of Male	-0.02	(0.68)	-0.00	(0.68)	(0.56)	0.02
Fraction of Married	-0.04	(0.73)	-0.04	(0.71)	(0.97)	-0.00
Household Income	-0.26	(0.72)	-0.26	(0.71)	(0.95)	0.00
Household Debt-to-Income Ratio	-0.03	(0.72)	0.00	(0.72)	(0.21)	0.04
Fraction with Bachelor or Higher	0.40	(0.72)	0.39	(0.74)	(0.74)	-0.01
Observations	1,279		1,279			

Panel E: Covariate Balance: 75th Percentile Threshold

	Treat = 0		Treat = 1			
	Mean	SD	Mean	SD	P-value	Std. Diff.
Log Population Above 65	0.13	(0.83)	0.12	(0.82)	(0.90)	-0.00
Vantage Score	-0.17	(0.89)	-0.20	(0.85)	(0.29)	-0.02
Fraction of Subprime	0.15	(0.89)	0.17	(0.84)	(0.35)	0.02
Fraction of Low Income	0.21	(0.89)	0.20	(0.89)	(0.76)	-0.01
Average Age	-0.02	(0.81)	-0.05	(0.79)	(0.23)	-0.03
Fraction of Male	-0.00	(0.79)	0.01	(0.78)	(0.77)	0.01
Fraction of Married	0.00	(0.78)	0.02	(0.76)	(0.59)	0.01
Household Income	-0.18	(0.80)	-0.19	(0.78)	(0.71)	-0.01
Household Debt-to-Income Ratio	-0.05	(0.81)	-0.02	(0.81)	(0.19)	0.03
Fraction with Bachelor or Higher	0.41	(0.76)	0.40	(0.78)	(0.67)	-0.01
Observations	1,918		1,918			

Table 6: Who did the policy help more?

This table presents difference-in-differences estimates of the heterogeneous effect of deputization on elder financial exploitation. The sample includes monthly observations for 2,557 counties from April 2012 to September 2019. *Ln(1+Elder Financial Exploitation Cases)* is the natural logarithm of one plus the number of elder financial exploitation cases in a county-month. *Post* is an indicator variable that equals to one after financial professionals are first empowered to halt suspicious transactions, either because a state adopts the Model Act or FINRA passes Rule 2165. All variables that are interacted with *Post* are indicator variables that equal to one if a county characteristic is above the national median. *Income Larger 200k* is an indicator variable that equals to one if a county has an above-median fraction of individuals with income higher than $200-thousand dollars. *Mean Retirement Income (Vantage Score)* is an indicator variable that equals to one if the average retirement income (credit score) in a county is above the national median. *Married (Female)* is an indicator variable that equals to one if a county has above-median fraction of married (female) seniors. *Pop 85 Above/Pop 65 Above* is an indicator variable that equals to one if a county has an above-median fraction of 85+ population among its 65+ population. *Bachelor or Higher* is an indicator variable that equals to one if a county has an above-median fraction of adults with a bachelor degree or higher. *White, Asian, Black*, and *Hispanic* are indicator variables that equal to one if a county has an above-median fraction of White, Asian, Black, and Hispanic population, respectively. A detailed description of the control variables can be found in Table 4 legend. Standard errors, adjusted for clustering at the county level, are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Ln(1+Elder Financial Exploitation Cases)											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Post	-0.019**	0.001	-0.040***	-0.063***	-0.033**	-0.042***	-0.017*	-0.083***	0.007	-0.027**	-0.001	-0.031
	(0.008)	(0.008)	(0.010)	(0.014)	(0.013)	(0.013)	(0.009)	(0.015)	(0.007)	(0.012)	(0.008)	(0.034)
Post x Income Larger 200k	-0.047**											0.001
	(0.019)											(0.020)
Post x Mean Retirement Income		-0.072***										-0.023
		(0.019)										(0.018)
Post x Vantage Score			-0.020									-0.029
			(0.019)									(0.020)
Post x Married				0.053***								0.034*
				(0.017)								(0.018)
Post x Female					-0.026							-0.002
					(0.018)							(0.017)
Post x Pop 85 Above/Pop 65 Above						0.008						0.006
						(0.018)						(0.018)
Post x Bachelor or Higher							-0.049***					-0.022
							(0.019)					(0.019)
Post x Pop White								0.079***				0.058**
								(0.018)				(0.029)
Post x Asian									-0.070***			-0.016
									(0.019)			(0.017)
Post x Black										-0.049***		-0.003
										(0.018)		(0.029)
Post x Hispanic											-0.063***	-0.019
											(0.019)	(0.017)
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.51	0.50	0.50	0.52
# Counties	2557	2557	2557	2557	2557	2557	2557	2557	2557	2557	2557	2557
Observations	225016	225016	225016	225016	225016	225016	225016	225016	225016	225016	225016	225016

Table 7: Welfare Effects

This table presents difference-in-differences estimates of the effect of deputization on senior financial outcomes. The sample includes annual observations for 762,709 individuals that are 65 years of age or older from 2010 to 2019. *I(Bankruptcy)*100* is an indicator variable that equals to 100 if an individual files for bankruptcy in a given year. *Post* is the fraction of months in a year that the elder protection policy is in effect in the state the individual lives. *Vantage Score* is the individual's credit score. *Age* is the individuals age in years. *Est. HH Income* is Experian's estimate of the individual's household income. *Married* and *Female* are indicator variables that equal to one if an individual is married or female, respectively. Standard errors, adjusted for clustering at the individual level, are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	I(Bankruptcy)*100		
	(1)	(2)	(3)
Post	-0.076	-0.104**	-0.116***
	(0.050)	(0.050)	(0.038)
Vantage Score		-2.984***	-0.602***
		(0.028)	(0.033)
Age		-5.882***	-2.866***
		(0.054)	(0.304)
Est. HH Income		-0.937***	0.011
		(0.021)	(0.029)
Married		0.133***	-0.010
		(0.028)	(0.017)
Female		0.064*	
		(0.033)	
Constant	2.808***	11.532***	6.505***
	(0.022)	(0.087)	(0.359)
Individual FE	No	No	Yes
Census Tract FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adjusted R^2	0.06	0.09	0.76
# Individuals	762709	762709	762709
Observations	4629098	4629098	4629098

Table 8: Role of the Investment Advisery Industry

This table studies the role of the investment advisery industry in curbing senior financial exploitation. The sample includes monthly observations for 2,557 counties from April 2012 to September 2019. *Ln(1+Elder Financial Exploitation Cases)* is the natural logarithm of one plus the number of elder financial exploitation cases in a county-month. *Post* is an indicator variable that equals to one after financial professionals are first empowered to halt suspicious transactions, either because a state adopts the Model Act or FINRA passes Rule 2165. *High Per Capita Investment Advisers (Brokers)* is an indicator variable that equals to one if a county has an above median per capita investment advisers (brokers). *High % Dual-Registered Advisers* is an indicator variable that equals to one if a county has an above-median fraction of investment advisers dual-registered as brokers. *High Complaints-Per-Adviser* is an indicator variable that equals to one if a county has an above median number of complaints per adviser. All regressions include additional time-varying county control variables, including the natural log of the number of persons 65 years of age or older, average credit score, fraction of subprime borrowers, fraction of low income individuals, average age, fraction of male individuals, fraction of married individuals, household income, household debt-to-income ratios, and fraction with bachelor or higher. Standard errors, adjusted for clustering at the county level, are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Ln(1+Elder Financial Exploitation Cases)				
	(1)	(2)	(3)	(4)	(5)
Post	-0.006	-0.011	-0.005	-0.038***	-0.003
	(0.008)	(0.008)	(0.008)	(0.011)	(0.009)
Post x High Per Capita Investment Advisers	-0.069***		-0.068***	-0.054***	-0.071***
	(0.020)		(0.024)	(0.018)	(0.020)
Post x High Per Capita Brokers		-0.054***	-0.003		
		(0.020)	(0.024)		
Post x High % Dual-Registered Advisers				0.054***	
				(0.015)	
Post x High Complaints-Per-Adviser					-0.007
					(0.020)
Controls	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.50	0.50	0.51	0.51	0.51
# Counties	2557	2557	2557	2557	2557
Observations	225016	225016	225016	225016	225016

Table 9: Was there increased monitoring from regulatory authorities?

This table studies whether empowerment of financial professionals to halt suspicious disbursements coincides with increases in monitoring by regulatory authorities of investment advisers and brokers. More specifically, we test whether there are coinciding increases in regulatory actions, customer complaints, and criminal charges filed against advisers and brokers. The sample includes monthly observations for 2,557 counties from April 2012 to September 2019. *Ln(1+Regulatory Actions)* is the natural logarithm of one plus the number of regulatory actions taken against advisers and brokers. A regulatory action is a sanction taken by the regulator against an adviser or broker, for example, permanently barring him or her from registering with a state's security division. *Ln(1+Customer Complaints)* is the natural logarithm of one plus the number of customer complaints filed against advisers and brokers. *Ln(1+Criminal Activities)* is the natural logarithm of one plus the number of criminal charges filed against advisers and brokers. Criminal charges include tax fraud and mail fraud. *Post* is an indicator variable that equals to one after financial professionals are first empowered to halt suspicious transactions, either because a state adopts the Model Act or FINRA passes Rule 2165. All regressions include additional time-varying county control variables, including the natural log of the number of persons 65 years of age or older, average credit score, fraction of subprime borrowers, fraction of low income individuals, average age, fraction of male individuals, fraction of married individuals, household income, and household debt-to-income ratios. Standard errors, adjusted for clustering at the county level, are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
	Ln(1+Regulatory Actions)	Ln(1+Customer Complaints)	Ln(1+Criminal Activities)
Post	0.00050	0.00072	-0.00006
	(0.00036)	(0.00126)	(0.00022)
Controls	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Adjusted R^2	0.05	0.32	0.01
# Counties	2557	2557	2557
Observations	225016	225016	225016

Table 10: Religious Adherents and Congregations

This table studies whether and how the effect of deputization varies with counties' religious adherents per capita and religious congregations per capita. The sample includes monthly observations for 2,557 counties from April 2012 to September 2019. *Ln(1+Elder Financial Exploitation Cases)* is the natural logarithm of one plus the number of elder financial exploitation cases in a county-month. *Post* is an indicator variable that equals to one after financial professionals are first empowered to halt suspicious transactions, either because a state adopts the Model Act or FINRA passes Rule 2165. *High Adherents (Congregations) Per 1000* is an indicator variables that takes a value of one if a county has above median number of religious adherents (congregations) per thousand population. All regressions include additional time-varying county control variables, including the natural log of the number of persons 65 years of age or older, average credit score, fraction of subprime borrowers, fraction of low income individuals, average age, fraction of male individuals, fraction of married individuals, household income, household debt-to-income ratios, and fraction with bachelor or higher. Standard errors, adjusted for clustering at the county level, are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively

	Ln(1+Elder Financial Exploitation Cases)		
	(1)	(2)	(3)
Post	-0.059***	-0.065***	-0.074***
	(0.015)	(0.017)	(0.019)
Post x High Adherents Per 1000	0.045**		0.020
	(0.018)		(0.017)
Post x High Congregations Per 1000		0.069***	0.065***
		(0.018)	(0.018)
Controls	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Adjusted R^2	0.50	0.51	0.51
# Counties	2557	2557	2557
Observations	225016	225016	225016

Table 11: Tenure in the Profession and in the Community

This table studies whether the effect of deputization varies with advisers' (Panel A) and brokers' (Panel B) tenure in the profession, tenure in the county, and tenure at a firm. The sample includes monthly observations for 2,557 counties from April 2012 to September 2019. *Ln(1+Elder Financial Exploitation Cases)* is the natural logarithm of one plus the number of elder financial exploitation cases in a county-month. *Post* is an indicator variable that equals to one after financial professionals are first empowered to halt suspicious transactions, either because a state adopts the Model Act or FINRA passes Rule 2165. *High Time in County*, *High Time in Profession*, and *High Time at Firm* are indicator variables that equal to one if the average time advisers or brokers have been in the county, profession, or firm, respectively, is above the national median as of December 2015. *High # of State Registrations Per Adviser* is an indicator variable that equals to one if the average number of states advisers are registered to work in exceeds the national median as of December 2015. Note, we do not have these state-registration data for brokers. All regressions include additional time-varying county control variables, including the natural log of the number of persons 65 years of age or older, average credit score, fraction of subprime borrowers, fraction of low income individuals, average age, fraction of male individuals, fraction of married individuals, household income, household debt-to-income ratios, and fraction with bachelor or higher. Standard errors, adjusted for clustering by county, are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Investment Advisers					
	Ln(1+Elder Financial Exploitation Cases)				
	(1)	(2)	(3)	(4)	(5)
Post	-0.016	-0.021**	-0.021*	-0.074***	-0.053***
	(0.011)	(0.010)	(0.012)	(0.014)	(0.015)
Post x High Time in County	-0.048***				-0.037
	(0.018)				(0.023)
Post x High Time in Profession		-0.036**			0.007
		(0.018)			(0.025)
Post x High Time at Firm			-0.036**		-0.015
			(0.018)		(0.024)
Post x High # of State Registrations Per Adviser				0.084***	0.083***
				(0.016)	(0.017)
Controls	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.50	0.50	0.50	0.51	0.51
# Counties	2557	2557	2557	2557	2557
Observations	225016	225016	225016	225016	225016

Panel B: Brokers				
	Ln(1+Elder Financial Exploitation Cases)			
	(1)	(2)	(3)	(4)
Post	-0.042**	-0.038**	-0.048***	-0.045**
	(0.016)	(0.015)	(0.018)	(0.019)
Post x High Time in County	0.007			0.004
	(0.021)			(0.021)
Post x High Time in Profession		-0.002		-0.028
		(0.020)		(0.025)
Post x High Time at Firm			0.015	0.034
			(0.024)	(0.031)
Controls	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.50	0.50	0.50	0.50
# Counties	2557	2557	2557	2557
Observations	225016	225016	225016	225016

Table 12: Form ADV Interactions

This table studies whether the effect of deputization on elder financial exploitation varies with how advisers charge clients for services. Characteristics of registered investment adviser firms are matched to individual adviser representatives and then averaged over individuals working in a specific county. We only have Form ADV data for advisers with more than $100M of assets under management, as smaller firms do not register with the SEC. We omit counties when we have no data on representatives' firms. The sample includes monthly observations for 2,225 counties from April 2012 to September 2019. *Ln(1+Elder Financial Exploitation Cases)* is the natural logarithm of one plus the number of elder financial exploitation cases in a county-month. *Post* is an indicator variable that equals to one after financial professionals are first empowered to halt suspicious transactions, either because a state adopts the Model Act or FINRA passes Rule 2165. *High Compensation % AUM* is an indicator variable that equals to one if the firm charges fees based on the assets under management. *High Compensation Hourly* is an indicator variable that equals to one if the firm charges an hourly fee for services. *High Compensation Commissions* is an indicator variable that equals to one if the firm charges commissions. Standard errors, adjusted for clustering by county, are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Ln(1+Elder Financial Exploitation Cases)		
	(1)	(2)	(3)
Post	-0.070**	-0.067*	-0.049
	(0.035)	(0.038)	(0.037)
Post x High Compensation % AUM	0.040	0.036	0.029
	(0.037)	(0.036)	(0.036)
Post x High Compensation Hourly		0.005	0.012
		(0.020)	(0.023)
Post x High Compensation Commissions			-0.028
			(0.022)
Controls	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Adjusted R^2	0.52	0.52	0.52
# Counties	2225	2225	2225
Observations	195800	195800	195800

Appendix A. Robustness

Figure A1: Main Effect Dropping Each State

This figure shows the distribution of the estimated policy effect in Table 4 Column (4) when dropping one state at a time. The y-axis is the fraction of the sample that has a coefficient that falls within a specific bin's range. The figure shows that the result is not driven by any one state.

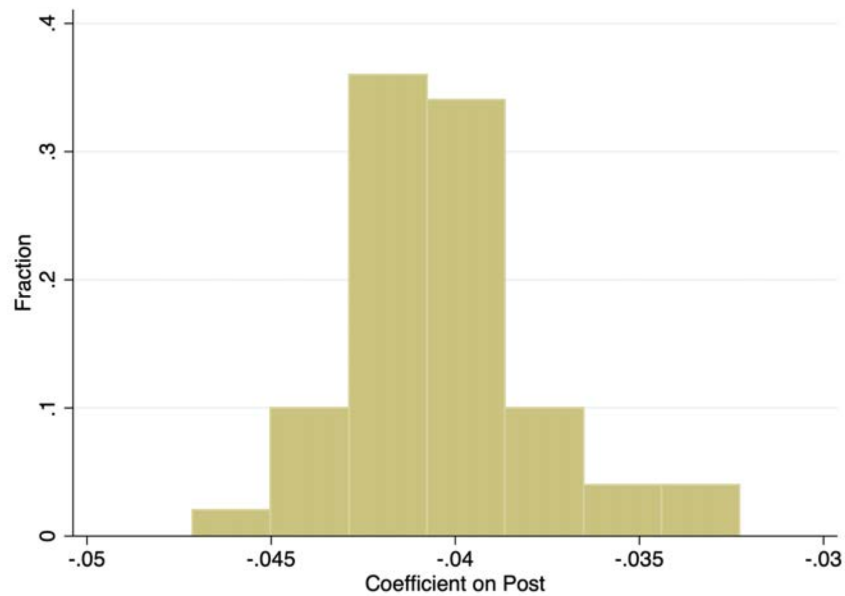


Table A1: Timing of Adoption of the Model Act and State Characteristics

In this table, we model the timing of when states adopt the Model Act using state characteristics. We limit the analysis to the 24 states that have adopted the Model Act by 2019. States adopted senior protection legislation in a staggered manner during our sample period (April 2012 - September 2019). The outcome variable, *Group of Adoption*, is equal to 1 for the earliest adopting state, 2 for the second earliest adopting state, and so on. If multiple states adopt the Model Act in the same month, then those states receive the same group number. *Number of Elder Exploitation Cases Per 1000* measures the number of elder exploitation cases per 1,000 population that are age 65 and above. *Frac Pop Abovve 65* measures the fraction of population that are 65 years of age or older. *Average Household Income (Credit Score)* measures the average household income (credit score) in a state. *Fraction of Married (Male)* measures the fraction of population in a state that is married (male). All variables on the x-axis are measured as of 2015, the year before the Model Act was finalized.

	Group of Adoption (1 = Earliest)					
	(1)	(2)	(3)	(4)	(5)	(6)
Elder Financial Exploitation Cases Per Capita	-0.006					
	(0.060)					
Fraction of Population 65+		0.178				
		(0.465)				
Average Household Income			0.155			
			(0.123)			
Average Credit Score				0.058		
				(0.053)		
Fraction of Married					0.135	
					(0.265)	
Fraction of Male						0.629
						(1.104)
R^2	0.00	0.01	0.07	0.05	0.01	0.01
# States	24	24	24	24	24	24

Table A2: Effects of Deputization on Elder Financial Exploitation: Pre-FINRA Rule 2165

This table presents difference-in-differences estimates of the effect of the deputizing financial professionals on elder financial exploitation. The sample only includes months prior to February 2018, the effective month for the FINRA Rule 2165. *Post* is an indicator variable that equals to one after a state adopts the Model Act. The outcome variable is the natural logarithm of one plus the number of elder financial exploitation cases in a county-month. A detailed description of the control variables can be found in Table 4 legend. Standard errors, adjusted for clustering at the county level, are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively

	Ln(1+Elder Financial Exploitation Cases)			
	(1)	(2)	(3)	(4)
Post	-0.062**	-0.034**	-0.052***	-0.048***
	(0.025)	(0.014)	(0.010)	(0.010)
Log Pop Above 65		0.227***	0.235***	1.159***
		(0.007)	(0.007)	(0.196)
Vantage Score		-0.046***	-0.029**	0.077***
		(0.013)	(0.014)	(0.015)
Fraction of Subprime		0.007	0.012	-0.020**
		(0.012)	(0.011)	(0.009)
Fraction of Low Income		0.048***	0.042***	0.028***
		(0.008)	(0.007)	(0.006)
Average Age		-0.013***	-0.012**	-0.059***
		(0.005)	(0.005)	(0.008)
Fraction of Male		0.005*	0.000	0.008**
		(0.003)	(0.003)	(0.003)
Fraction of Married		0.011**	0.001	0.018***
		(0.005)	(0.004)	(0.004)
Household Income		0.082***	0.057***	0.009
		(0.010)	(0.011)	(0.014)
Household Debt-to-Income Ratio		-0.022***	-0.027***	0.001
		(0.005)	(0.005)	(0.005)
Fraction with Bachelor or Higher		0.157***	0.156***	0.163***
		(0.009)	(0.009)	(0.009)
Constant	0.209***	0.235***	0.234***	0.251***
	(0.007)	(0.004)	(0.004)	(0.003)
Year-Month FE	Yes	Yes	Yes	Yes
State FE	No	No	Yes	No
County FE	No	No	No	Yes
Adjusted R^2	0.07	0.36	0.37	0.47
# Counties	2557	2557	2557	2557
Observations	178990	178990	178990	178990

Appendix B. Decomposition of Staggered Diff-in-Diff Coefficient

Recent developments in the econometric literature give us guidance on how to best implement the generalized difference-in-difference empirical strategy. We follow the suggestions of Goodman-Bacon (2018) on how to decompose our difference-in-difference estimator, and find qualitatively similar results when we rely on different sources of variation.

According to Goodman-Bacon (2018), the generalized difference-in-difference model differs from canonical models that contain only two time periods ("pre" and "post") and two groups ("treatment" and"control"). In the generalized difference-in-difference setting, researchers explore three distinct sources of variations: the difference in treatment timing across the timing group, the timing group compared with the never-treated group, and the timing group compared with the always-treated group. Goodman-Bacon (2018) shows that the generalized difference-in-difference estimator is a weighted average of all possible two-group/two-period difference-in-difference estimators in the data. As in any least squares estimator, the weights are proportional to group sizes and the variance of the treatment dummy within each pair. Treatment variance is highest for groups treated in the middle of the panel and lowest for groups treated at the extremes.

Summing the weights on the timing comparisons versus treated/untreated comparisons quantifies how much of the variation comes from timing. Using Goodman-Bacon (2018)'s decomposition code, we find that our estimator is mainly driven by variations within the timing group. As shown in Table A3 Panel A, the sum of weight on the 2x2 estimators within the timing group is 92%, and the average coefficient estimate is -0.04. The estimators derived from differences between the timing group and the always-treated group receives a weight of only 8%, and an average coefficient estimate of -0.22.[35]

In the current specification, we do not have any never-treated states in the data. As a robustness test, we implement another specification where we drop all periods after February 2018, the month of the FINRA policy implementation, and hence all states that are treated after the FINRA policy effectively become control states (i.e. never-treated group). Using this specification, in Table A3 Panel B and Figure A2, we find a 5.1% reduction in county-month number of senior financial exploitation cases. The decomposition shows that the main source of variation comes from the differences between the timing group and the never-treated group, which receives a weight of 80% and an average 2x2 difference-in-difference coefficient estimate of -0.07. Instead, the average coefficient within the timing group is -0.02,

[35]We use the Stata package "bacondecomp" written by Andrew Goodman-Bacon to conduct the decomposition analysis. We are able to replicate all results using a different Stata package, "ddtiming", written by Thomas Goldring.

with a weight of 18%. The consistently negative coefficient estimates across specifications and sources of variations lend robustness to our empirical finding.

Table A3: Goodman-Bacon Decomposition

This table shows the Goodman-Bacon decomposition of staggered difference-in-difference regression coefficient estimates (Goodman-Bacon, 2018). We provide a detailed description of the methodology in the Appendix B. In Panel A, we include all time periods in our sample to conduct this analysis. The empirical specification is the same with the specification used in Table 4 Panel A Column (4). In Panel B, we exclude all observations after February 2018, the date of the FINRA Rule 2165 adoption, to allow for an additional source of variation coming from the "Never Treated" group.

Panel A: Entire Sample

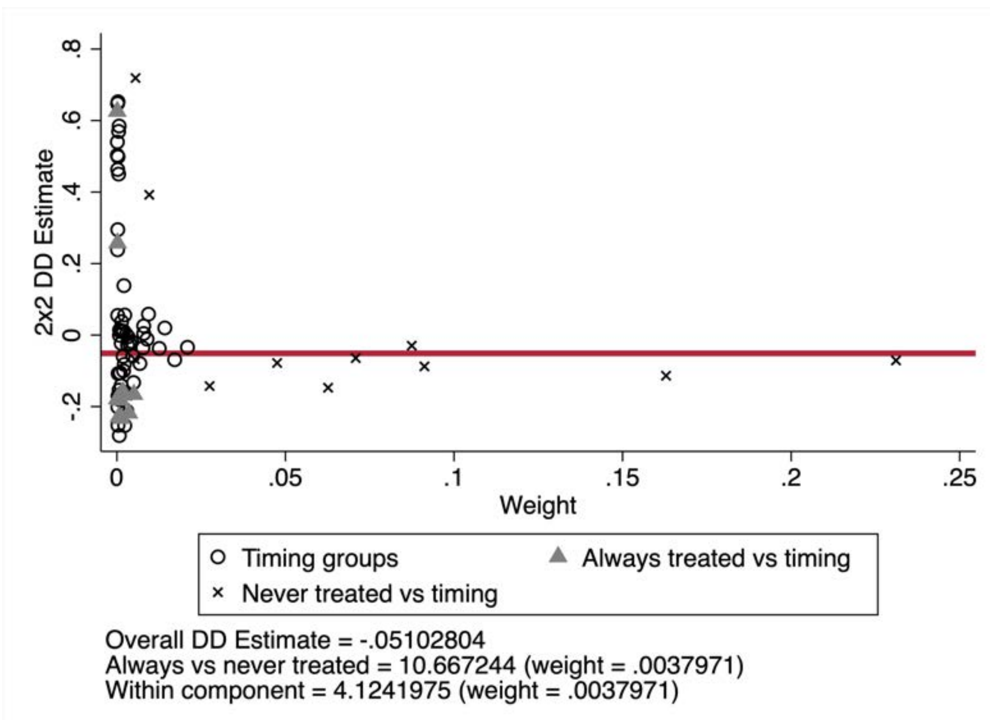
Variation	**Beta**	**Weight**
Timing Groups	-0.0408	0.9178
Always v. Timing	-0.2227	0.0803
Within	7.9540	0.0019

Panel B: Excluding Observations after February 2018

Variation	**Beta**	**Weight**
Timing Groups	-0.0257	0.1774
Always v. Timing	-0.1737	0.0175
Never v. Timing	-0.0738	0.8012
Always v. Never	10.6672	0.0000
Within	4.1242	0.0038

Figure A2: Goodman-Bacon Decomposition

This table shows graphically the Goodman-Bacon decomposition of staggered difference-in-difference regression coefficient estimate (Goodman-Bacon, 2018). We provide a detailed description of the methodology in the Appendix B. The empirical specification used to produce the graph is the specification used in Table A3 Panel B. When we ran the specification used in Panel A, the Stata package "bacondecomp" produces only table outputs (shown in Table A3 Panel A) but no graph.



Appendix C. Factiva Searches

Table A4: Details Regarding Factiva Searches

In this table, we present the text, date, region, timestamp, and other details of the searches that we conduct on Factiva's global news search engine. "And" and "Or" are operational words.

Panel A	
Text	(adviser Or advisor) And (halt Or delay) And (financial abuse Or financial exploitation)
Date	In the last 5 years
Source	All pictures Or All publications Or All web news Or All multimedia Or All blogs
Author	All authors
Company	All companies
Industry	All Industries
Region	United States
Language	English
Results Found	67
Timestamp	19 April 2020 1:58 GMT
Panel B	
Text	(adviser Or advisor) And (suspicious transaction) And (financial abuse Or financial exploitation)
Date	In the last 5 years
Source	All pictures Or All publications Or All web news Or All multimedia Or All blogs
Author	All authors
Company	All companies
Industry	All Industries
Region	United States
Language	English
Results Found	2
Timestamp	16 April 2020 23:16 GMT
Panel C	
Text	(adviser Or advisor) And (elder financial exploitation Or elder financial abuse Or elder financial fraud)
Date	In the last 5 years
Source	All pictures Or All publications Or All web news Or All multimedia Or All blogs
Author	All authors
Company	All companies
Industry	All Industries
Region	United States
Language	English
Results Found	209
Timestamp	16 April 2020 23:08 GMT