Deputization

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Abstract

Deputization is a permissive policy that asks agents to help screen for dangerous activities without providing explicit incentives. Its success, then, depends on other extrinsic or intrinsic motives. To assess its potential efficacy, we exploit the staggered adoption of recent laws that deputized financial professionals to help fight elder financial abuse. This is a widespread and pernicious problem that is hard to police. We find that deputization led to a 4%-6% decrease in suspected cases of elder abuse and a significant drop in personal bankruptcies. We discuss several possible mechanisms through which deputization acted in this setting.

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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 motivations (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. It has 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 large-scale, quasi-natural experiment targeting financial abuse of the elderly. This is not only a pervasive and growing problem, it is pernicious.[2] Elder abuse is hard to police because the perpetrators are often people close to the victim like family members and caregivers.

Recently, regulators deputized financial professionals to assist with this problem through the NASAA Model Act and FINRA Rules 2165 and 4512.[3] Both of these rule changes granted new tools to fight elder abuse. The first is the express authority to reach out to a

[1]Many economists have suggested that agents conform to ethical codes rather than act egoistically (e.g. Arrow, 1988; Brennan, 1994; Bénabou and Tirole, 2003; 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]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.

[3]Financial professionals included a broad set of agents, including money managers, retirement planners, brokers, and investment advisers working either at depository institutions or independent securities firms. In fact, five states explicitly deputized *all* types of financial professionals: Delaware, Kentucky, Texas, Virginia, and Washington.

trusted contact to discuss red flags, confirm mental and physical health status, and confirm the identity of any legal guardian.[4] The second is the authority to delay the disbursement of funds that appear suspicious for financial abuse. This allows time to investigate the proposed disbursement before monies are lost. In practice, however, an actual delay of disbursements is only used as a last resort, after a professional looks into the details of the situation.[5] The ability to delay and investigate are often used hand-in-hand.

Both regulations are examples of deputization because they are permissive rather than mandatory. Regulators chose 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."[6] Importantly, these rule changes did not alter the existing requirement that financial professionals report elder financial exploitation to the U.S. Treasury. 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.

We amass a large dataset: reports of suspected elder financial exploitation from the Department of Treasury[7], the employment history of the entire universe of registered brokers and advisers from the Financial Industry Regulatory Authority (FINRA) and the Securities and Exchange Commission (SEC), credit bureau reports from older adults in the United

[4]It is important to note that trusted contacts are unable to view account information, execute transactions or inquire about account activity unless they are already an authorized party. While financial institutions have been permitted to disclose consumer information to appropriate regulators in the event of elder financial exploitation since the Graham-Leach-Bliley Act of 1999, these recent rule changes newly allow discussing issues with a trusted contact and also provide clear protections from lawsuits connected to such disclosures. Source: https://files.consumerfinance.gov/f/201309_cfpb_elder-abuse-guidance.pdf

[5]In conversation with us, the head of Alabama's securities division stated that nine out of ten cases are handled by reaching out to a trusted contact and using the ability to halt a disbursement as a deterrent.

[6]NASAA received comment letters during the formation of the Model Act encouraging there to be a penalty. For example, the Public Investors Arbitration Bar Association writes, "In order to enforce the obligations that should be created by the Model Act, there should be inclusion of a penalty." However, ultimately, they chose not to include incentives like this.

[7]Reported cases frequently involve actual monetary losses. 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.

States, county-level data on congregations and adherents from the U.S. Religion Census, media coverage for elder abuse during 2015-2020 from Factiva, social connectedness measures from Facebook, and county-level data from the U.S. census.

The dependent variable that we analyze is the county-level, monthly frequency of elder abuse. Alternatively, one could imagine using the incidence of halted disbursements or trusted-party contacts to study the effectiveness of the new regulation. However, an analysis of these actions may mischaracterize the effectiveness of deputization because the ability to halt disbursements and reach out to trusted contacts interacts with other hidden actions that are helpful in curbing abuse.[8] For example, financial professionals may deter exploitation by communicating to clients and potential perpetrators the new safeguards. Such hidden actions prevent egregious activity before it is attempted, eliminating the need to make reports to regulatory agencies. So, the observable equilibrium outcome that best captures the deterrent role of deputization is the frequency of elder abuse cases.

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.[9] The result is robust to including county and month fixed effects, to dropping any state, and to matching treated and non-treated counties on pre-treatment characteristics. Randomizing the treatment dates results in no effect, and there is no drop in reports from money services businesses, which are not deputized. The drop is more pronounced for elder exploitation involving disbursements of cash, such as fund transfers, debit cards, and personal checks, than for exploitation involving other instruments, such as credit cards (used for purchases). Lastly, the drop in elder financial exploitation is more pronounced in counties with a higher per capita presence of financial professionals.

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). Bankruptcy among the elderly may be especially costly since society typically needs to shoulder the burden of housing and caring for elders without resources for their remaining life. We find that this policy of deputization was associated with a significant reduction in the annual frequency of bankruptcy among elders, and was particularly important for individuals 80 years of age or older.

[8] Also, data on halting activity is fraught with error because documentation is often incomplete or unavailable. In discussions with FINRA, NASAA, and Texas APS, it is not standard practice to document halts in case records and those that are may not be shared externally due to privacy agreements.

[9] In our sample, there are 0.8 cases per county-month on average. This translates into a reduction of 981 ($4\% \times 0.8 \times 2{,}557 \times 12$) to 1,472 cases per year.

It is natural to consider why deputization works, acknowledging that it could be different in other applications. We discuss several potential channels, which include strong personal relationships or social networks (Leider et al., 2009), financial rewards (Egan, 2019), legal ramifications (Sunstein, 1996), a sense of public duty (Carlin, Dorobantu, and Viswanathan, 2009), a moral imperative (Carlin and Gervais, 2009), and a desire for publicity (Tadelis, 1999).[10] We run a series of cross-sectional regressions with county-level characteristics and show evidence that tailored financial advice appears to provide a protective mechanism. This may be driven by higher AUM per client or more familiarity them. We also find evidence that suggests that stronger existing community connections, as measured by Facebook links or the number of religious congregations, make protection from deputies less important.

Finally, 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, Gerken, and Graham, 2018; Charoenwong, Kwan, and Umar, 2019). In fact, financial professionals are culpable for preying on the elderly (Egan, Matvos, and Seru, 2019).[11] Importantly, we find no evidence that deputies use their new authorities to abuse the elderly, as there is no evidence of an increase in customer complaints or regulatory actions against the deputies. Happily, our results suggest that empowering financial professionals can help combat elder abuse.

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 adult's funds, property, or assets."[12] 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.[13]

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

[10] Additionally, these may not act in isolation from each other. For example, as Carlin, Dorobantu, and Viswanathan (2009) show, the law can either be a complement or a substitute for public trust formation.

[11] For example, a Louisville investment adviser defrauded elderly customers of over $800,000. Source: www.justice.gov/usao-wdky/pr/louisville-financial-planner-charged-during-nationwide-elder-fraud-sweep-more-250

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

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

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 Alzheimer's 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.[14]

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.[15] 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.[16]

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.[17]

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 ($50,200) 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, Latino, poor, and isolated older adults were disproportionately victimized.[18]

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

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

[16] 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.

[17] 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.

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

2.2. *Financial Professionals*

The financial professionals in our setting include a broad set of agents, including money managers, retirement planners, brokers, and investment advisers working either at depository institutions or independent securities firms. As we describe in Section 3, five states expressedly deputized *all* types of financial professionals (Delaware, Kentucky, Texas, Virginia, and Washington), while other states included brokers and investment advisers providing a variety of services. This subsection provides background on these deputies.

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, requiring advisers to put their clients' interests first. 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. RIAs may be standalone firms or divisions of larger financial institutions, such as bank holding companies (e.g. Morgan Stanley Wealth Management managed $735 billion in assets in 2017 per its Form ADV).

FINRA oversees broker-dealers, which employ brokers. The Securities Exchange Act of 1934 defines a broker-dealer as any "company engaged in the business of buying and selling securities on behalf of its clients, for its own account (as dealer), or both." Broker-dealers may be standalone firms or divisions of larger financial institutions, such as bank holding companies. Broker-dealers typically charge commissions and product fees, whereas registered investment advisers charge fees based on 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. Conflicts of interest are potentially higher for brokers than advisers.

Approximately 50% of broker representatives are dual-registered as investment advisers and about 85% 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 similarly granted financial professionals serving an elderly client the authority to reach out to trusted contacts and if needed, the power to halt disbursements of funds. Both regulations are permissive (not requiring participation) and do not provide explicit incentives. Before these rules were passed, professionals were required to report suspicious disbursements to the U.S. Treasury. But, because monies were often hard to recover during investigations, simple reporting did little to limit financial loss.[19] The two rules vary in certain other terms of their implementation and the types of financial professionals covered. These differences are summarized in Table I and detailed below.

[Insert Table I Here]

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 provisions enhancing the ability of these financial professionals to protect the elderly is the authority to reach out to a specified trusted contact and 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

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

senior.[20] 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 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 II, 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.[21] 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.

[Insert Table II Here]

Figure I Panel A shows graphically the staggered adoption of the Model Act or similar provisions across U.S. states.

[Insert Figure I Here]

[20]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 adult's 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."

[21]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.

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, although the majority of the states adopting the Model Act 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 Rules 2165 and 4512

State regulation of broker-dealers exists in parallel with the Financial Industry Regulatory Authority (FINRA), a federally-sanctioned self-regulatory organization. In February 2017, FINRA proposed new FINRA Rule 2165 (Financial Exploitation of Specified Adults) and amendments to FINRA Rule 4512 (Customer Account Information). The Securities and Exchange Commission (SEC) approved them both in March 2017. The new rules became effective on February 5, 2018.

The amendments to FINRA Rule 4512 require broker-dealers to make reasonable efforts to implement a "trusted contact" system. FINRA Rule 2165 allows 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.[22] Upon placing a hold, FINRA Rule 2165 requires the broker-dealer to immediately initiate an internal review of the facts and circumstances.[23] On February 5, 2018, the rule was approved by the SEC and became effective nationwide.

The essence of the FINRA Rules 2165 and 4512 is similar to that of the Model Act, but FINRA Rules 2165 and 4512 do not apply to investment advisers, while the Model Act applies to both broker-dealers and investment advisers. Additionally, FINRA Rules 2165 and 4512 do not provide immunity to brokers acting according to the rule change because it is not a state or federal law, while states adopting the Model Act do provide immunity.

[22] 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 it's a scam, he or she can then temporarily pause the disbursement and investigate further.

[23] Although the rule applies to the disbursement of securities, it does not apply to transactions in securities. For example, FINRA Rule 2165 would not apply to a customer's 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. FINRA is currently discussing an amendment to the rule change that would allow brokers to halt transactions as well.

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, 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.[24] As of December 2002, rule 31 CFR § 1023.320 requires reporting by broker-dealers. In 2015, it was proposed that investment advisers also become mandatory reporters to FinCEN, but the rules were never adopted. However, approximately 85% of investment advisers are dual-registered as brokers and are thus already required to report. Additionally, advisers largely work for or with financial institutions that are already subject to SARs reporting requirements. For example, advisers may work in a division of a bank holding company, execute trades through broker-dealers to purchase or sell client securities, and direct custodial banks to transfer assets. Most importantly, the reporting requirements to FinCEN by any financial professional did not change with a state's adoption of the Model Act or with FINRA's adoption of Rule 2165.[25]

In April 2012, FinCEN introduced electronic suspicious activity reporting with a designated category for "elder financial exploitation." We collect the total number of reported cases in a county in a month. The count is broken down by the type of reporting institution, financial product involved (e.g. fund transfer), financial instrument involved (e.g. debit card), and regulator overseeing the reporting financial institution. Reports are tied to the county in which the victim resides.[26] Figure II shows that reports of elder financial exploitation have been increasing ever since the category was introduced in 2012.

[Insert Figure II Here]

[24] 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.

[25] 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."

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

Reporting suspicious activity is mandatory when a suspicious transaction involves above \$5,000 in funds or assets. If such a suspicious disbursement is attempted or occurs, then it must be reported. The rule changes we examine provide financial professionals with new tools to deter attempted abuse. Stranger scams may find it less profitable to target the elderly if they realize that trusted contacts or disbursement delays will interfere with their exploits. Financial professionals may also communicate the new safeguards in place to potential perpetrators close to the victim. If the tools help financial professionals deter exploitation, then the number of reported cases of financial exploitation to FinCEN may fall because the number of attempted suspicious disbursements declines.

4.2. Investment Advisers and Brokers

Because the Model Act deputizes 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, these 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 a detailed description of each customer complaint filed against an adviser and each regulatory action taken against an adviser as well as details about a variety of 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 2010 to 2019. The data 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, including age, credit score, estimated income, and debt characteristics including auto loans, mortgages, credit card debt, and medical debt. The data also provide the census tract the individual resides in, allowing us to know when an individual's community is treated. Individual identifiers allow for within person analyses.

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. Facebook Social Connectedness Index

We use a new dataset from Facebook to measure the strength of social ties in a county. The Social Connectedness Index is constructed using aggregated and anonymized information from the universe of friendship links between all Facebook users as of April 2016 (Bailey et al., 2018). The Social Connectedness Index between two locations i and j is defined as:

$$Social\,Connectedness_{i,j} = \frac{Facebook\,Connections_{i,j}}{Facebook\,Users_i \times Facebook\,Users_j} \tag{1}$$

Here, $Facebook\,Users_i$ and $Facebook\,Users_j$ are the number of Facebook users in locations i and j, and $Facebook Connections_{i,j}$ is the number of Facebook friendship connections between users in the two locations. $Social\,Connectedness_{i,j}$, thus, measures the relative probability of a Facebook friendship link between a given user in location i and a given user in location j. When i is equal to j, this index measures the social connectedness within a county. Locations are assigned to users based on not only public profile information (such as the stated city), but also device and connection information. Only friendship links among Facebook users who have interacted with Facebook over the prior 30 days are considered.

Facebook usage rates are high in the United States. Even among adults that are 65 years of age or older, the average usage rate is about 56% (Bailey et al., 2018). For younger adults, the usage rate is 87% on average.

4.5. 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. 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, such as children, members, and attendees who are not members.

Every decade, 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.[27] These proxies for religiosity are standard in the literature (Hout and Greeley, 1998; Grullon et al., 2009).

4.6. 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.

4.7. 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.

4.8. 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.

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

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. Figure II shows that the number of reported cases of elder financial exploitation in the FinCEN database is increasing markedly over time.

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 NASAA Model Act and the timing of FINRA Rules 2165 and 4512. Table II details when states adopted the Model Act. As noted before, there was no concomitant change in the reporting requirements of suspicious activity 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 and that were adopted in a staggered fashion.[28]

[28] The *Senior Safe Act* became federal law on May 24, 2018. It provides financial institutions with immunity for reporting potential exploitation of a senior citizen to regulators. It does not provide any tools (like the ability to reach out to a trusted contact or halt a suspicious disbursement). This rule change cannot explain our results because it becomes effective nationally at the same time. Our results are only identified off of policy changes implemented in a staggered fashion. To show this, in Appendix Table A3, we find similar results when only including sample months prior to February 2018.

We estimate models of the following form:

$$OUTCOME_{ct} = \alpha + \beta POST_{st} + \gamma' \mathbf{X}_{ct} + \eta_c + \eta_t + \epsilon_{ct} \tag{2}$$

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 reach out to a trusted contact and halt suspicious disbursements. Figure I Panel B shows variations in these treatment dates across states. The β on $POST_{st}$ measures the effect of the rule change.[29] $\mathbf{X}_{ct}$ 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. In specifications that interact $POST_{st}$ with a covariate of interest (e.g., $POST_{st}$ interacted with the number of investment advisers per capita in a county), we also include interactions between $POST_{st}$ and each control covariate to alleviate the possibility that the interaction of interest is biased by an omitted interaction with another covariate (Yzerbyt et al., 2004). 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. In all tables in the paper, we double-cluster standard errors at the state and month levels.[30]

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 III shows, in event time, no unusual changes in elder financial exploitation prior to the rule change, and a noticeable drop only upon passage.

[Insert Figure III Here]

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

[29] The staggered difference-in-difference approach uses three distinct sources of variation: 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. Because FINRA Rules 2165 and 4512 apply nationally, we do not have a never-treated group. See Appendix B for a decomposition of this effect by the source of variation, as outlined in Goodman-Bacon (2018).

[30] The key explanatory variable that we are doing statistical inference on and as such whose standard error we want to be accurate is more aggregated than our explanatory variables (state vs. county/individual). When this is the case, there are generally good, even mechanical reasons to expect the error term to be correlated within the aggregate unit. In these situations, standard practice is to cluster at the more aggregated level of the key explanatory variable (Abadie et al., 2017). Otherwise, the regression "thinks" we have more independent observations of $POST$ than we really do.

household income and credit scores, the share of the population that is male or married, and population. In Figure IV and Appendix Table A2 panel A, 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 result from idiosyncratic conventions by state legislators to meet at different times to set the effective dates for new laws.[31] Relatedly, in Appendix Table A2 panel B, we find little relation between state characteristics, such as population, and *whether* a state adopts the Model Act by 2019.

[Insert Figure IV Here]

5.2. Main Effects

We find that deputizing appears to be effective at deterring financial exploitation of the elderly. Table IV 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.[32] Column (1) shows a 6.3% decrease in financial exploitation in treated states. Columns (2) and (3) both show a 5.9% decrease when including state and county fixed effects, respectively, which account for geographic time-invariant characteristics. Columns (4) to (6) show similar results when including a number of time-varying county-level controls. Comparing columns (1) and (4) show that these controls are helpful in explaining variation in elder exploitation as the adjusted R^2 increases from 7% to 37% when including the controls. Overall, the estimated decline in financial exploitation remains quantitatively similar across specifications and is statistically significant at the 5% level. The economic magnitudes suggest an annual reduction of between 1,155 and 1,732 elder financial exploitation cases across the U.S.[33]

[Insert Table IV Here]

[31] For instance, in Florida, by September 2019, the bill had passed through Florida's House of Representatives twice, but not the state senate. The champion of the bill remarked that the legislative sessions were busier than usual and other bills took precedence. The champion of the bill also said, "There are a lot of moving parts as you go through the legislative process. If the legislative session closes before state representatives and senators pass the law, then the process restarts from square one. We fought a tough fight." The champion added that they will renew their efforts next year. See https://www.financial-planning.com/news/how-advisors-can-prevent-elder-financial-exploitation.

[32] 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

[33] A 4-6% reduction on an average of 0.8 cases per county-month is a reduction of 0.032-0.048 cases per county-month. Multiplying this value by 12 months a year and by 3,007 counties in the U.S. gives between 1,155 and 1,732 cases per year.

Table IV 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 any exploitation occurring 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 III, 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 IV).[34] So that each covariate receives an equal weight, we standardize them 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 V Panels A and B show that the estimates using matched county pairs are statistically significant and economically similar to those presented in Table IV. Table V Panels C-E report the covariate balance tables for each of the distance thresholds we employ, which show that paired counties are similar in observable aspects.

[Insert Table V Here]

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 IV Panel A Column (6) is robust to dropping any state. Appendix Figure A2 shows that there is no effect when randomizing treatment dates, which shows that the result is not a mechanical result of the econometric specification. Appendix Table A3 shows a similar drop when the sample is

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

cut off in January 2018, prior to enactment of FINRA Rules 2165 and 4512. Lastly, the results are unique to using suspicious activity reports related to elder financial exploitation. Appendix Table A4 columns (1) and (2) show no effect of the policy change on suspicious activity reports related to insider trading and terrorism financing. Hence, it is unlikely that reporting to FinCEN shifted more generally.

If the decline is a result of the policy, then the effect should be stronger for exploitation involving disbursements. Table VI, panel A, column (1) shows a large and significant decrease in exploitation involving debit cards, which can be used at banks to withdraw funds. By contrast, columns (2) through (7) show no effect on exploitation involving credit cards, home equity lines of credit (HELOCs), insurance, mutual funds, or prepaid access. Relatedly, panel B, shows the largest drop for abuse involving a fund transfer and U.S. currency. There is no effect on exploitation involving bank cashiers checks and money orders, which are already subject to strict scrutiny and primarily used for large purchases (e.g., autos, and homes).

[Insert Table VI Here]

The drop in elder financial exploitation is stronger where there are more deputies per capita. Consistent with this reasoning, Table VII, panel A, column (1) shows that the drop in elder abuse is greater in counties with more investment adviser representatives per capita. Moreover, panel B shows no significant effect on the number of reports of elder financial exploitation from money services businesses, which employ neither brokers nor advisers.

[Insert Table VII Here]

Examining the sensitivity of the effect to the presence of advisers and brokers suggests that the effect is more sensitive to the presence of advisers.[35] Specifically, Table VII, panel A, column (2) shows that the effect is not related the number of brokers per capita. The estimated coefficient is close to zero. Relatedly, column (3) shows that the policy effect is weaker when more advisers are dual-registered as brokers, and column (4) shows that the policy's effect is significantly weaker when there are more brokers per capita. (Note that the magnitudes in column (4) should be interpreted with caution as the correlation between the number of advisers and brokers in a county is 0.77.) Complementing these results, Table VII, panel B, column (3) shows no drop in the number of reports from securities (broker-dealer) firms. By contrast, column (1) shows a decline in the number of reports from depository institutions, which include bank holding companies that contain investment

[35]Note that both the number of advisers and number of brokers are standardized in Table VII, panel A, to allow for such a comparison.

advisery divisions. We discuss possible reasons for why deputization of advisers leads to a larger response in Section 6.

Our regression estimate of the policy's effect using the staggered difference-in-differences design is likely an underestimate. Figure III shows 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).

The initial drop in Figure III is consistent with advisers and brokers gaining the ability to prevent exploitation by contacting trusted contacts and threatening halts, which disincentivizes clients and perpetrators from attempting suspicious disbursements. The subsequent drift may be explained by a few reasons. First, it takes time for advisers and brokers to learn about the legislation, develop protocols for implementation, and provide training. State securities divisions have been organizing seminars for financial professionals to inform them about the rule change.[36] Second, the deterrence effect of allowing financial professionals to reach out to trusted contacts and to halt transactions may take time to become known among the perpetrators.[37]

5.3. 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). According to the National Center for Law and Elder Rights, "Older adults seeking to leave an abusive environment may need help protecting their limited income and resources from seizure by creditors and debt collectors."[38] According to Ohio Colleges of Medicine, "Financial losses can even bankrupt

[36]For example, in 2019, Colorado's securities division held 14 industry facing events using both webinars and in-person presentations. These events are targeted to front line financial professionals who have regular contact with clients. Likewise, Michigan's Corporations, Securities and Commercial Licensing Bureau also held two outreach seminars during 2018. The seminars had the primary goal of introducing investment advisers and broker-dealers to the new rules, discussing how these rules would affect their businesses, and how to handle suspected elder abuse within their client base. See the NASAA 2019 and 2020 Investment Adviser Section Report for more details.

[37]If the policy had created an empty threat and deputies did not act, we would expect potential perpetrators to ultimately learn that the law was ineffective. If this were the case, the resulting pattern of abuse cases would show an initial and transient drop and an eventual reversal. But, this is not what we find in the data.

[38]https://ncler.acl.gov/getattachment/Legal-Training/Consumer-Law-and-Elder-Abuse-Ch-Summary.pdf.aspx?lang=en-US

the victim and his family members, with society then paying to feed, house and care the elder for the remainder of his life."[39]

To examine changes in bankruptcy, we use individual-level credit information from Experian for a random sample of 1% of all individuals 18 years of age or older. We then follow these elderly individuals through time; our data spans 2010 to 2019. For each individual, we have annual credit information and the census tract (contained within counties) in which a person resides.

Table VIII presents the results. The outcome variable is an indicator variable that equals 100 if the individual has a bankruptcy event in year t. *Post* equals one in the year that either rule change went into effect in the state the individual lives. Columns (1) to (4) show a decline in the tendency to have a bankruptcy event for older individuals relative to younger individuals. All specifications include individual-level fixed effects and control for individuals' prior year credit scores, and the effect is statistically significant at the 1% level (with state level clustering). Columns (3) and (4) include census-tract by year fixed effects to account for unobservable local trends. According to Column (1), the tendency of having a bankruptcy event decreases by about 3 basis points after treatment (0.079 minus 0.11). The unconditional probability of having a bankruptcy each year is 0.46%, so this represents a 6.5% drop.

[Insert Table VIII Here]

6. Discussion of Possible Mechanisms

Here, we consider why deputization appears to work in our setting, and acknowledge that it could be different in other applications. There are a number of possibilities. Financial professionals may have monetary incentives to preserve their clients' wealth, since they often receive compensation based on assets under management (AUM). Alternatively, they may worry about their legal exposure if their client suffers harm or may have a desire for good publicity to attract future business. These are extrinsic incentives that are typically referred to as being egoistic (Carlin and Gervais, 2009).

Alternatively, intrinsic incentives might be important. Agents may be good deputies because they suffer dysutility for being unethical, or if they adhere to a moral code (e.g. Arrow, 1988; Brennan, 1994; Akerlof, 2007). Relatedly, the success of deputization might stem from deputies' personal relationships with their clients, because individuals are more willing to help those with whom they have a relationship, or community connections more

[39] https://grc.osu.edu/sites/default/files/inline-files/Preventing_Elder_Financial_Exploitation_by_Family_Members_Policy_Considerations_for_Ohio%5B1%5D.pdf

generally, because professionals in such communities are more likely to derive utility from the increases in the welfare of others (Leider et al., 2009).

Given this variety of possible explanations, we explore them by referring to our results so far or through additional cross-sectional regressions using county-level characteristics. But, as is typically true, more than one motive is likely to be responsible and the channels described here interact. As such, the results in this section are meant to be descriptive and not a horse race among competing theories.

6.1. Financial Incentives

In Table IX, we examine how the policy's effect relates to an adviser's compensation structure. These analyses use data 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 working for a firm (or branch of a firm) operating in that county.

[Insert Table IX Here]

If revenue preservation explains the incentive to be a deputy, then the effect should be larger when each client is more lucrative for the firm. Consistent with this reasoning, column (1) of Table IX shows that the effect is stronger when advisers serve wealthier clients (more AUM per client). Columns (2) to (4) show that the effect is unrelated to whether more advisers in a county charge fixed fees, commissions, or hourly fees, which may suggest a more transactional or temporary relationship with clients.

6.2. Legal Ramifications

Another egoistic motivation might be that financial professionals themselves would change behavior based on a fear of being more closely monitored, prosecuted, or facing more stringent regulation in the future. The adoption of the new laws may signal increased regulatory concern with elder financial exploitation and thus increased oversight and monitoring of advisers and brokers. If this were the case, then we would expect professionals to not only protect the elderly more, but also decrease their own egregious activity.

We examine the possible increased threat of monitoring in Table X 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.[40]

[Insert Table X Here]

Relatedly, 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 any sanctions the laws threaten or rewards the laws provide. For example, 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, even in the absence of enforcement. 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 similarly 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. However, this mechanism is unlikely to be the main explanation because Table VII suggests that the policy's effect varies significantly more with the number of advisers per capita than with the number of brokers per capita.

6.3. Publicity

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 SEC's Investment Adviser Public Disclosure (IAPD) website nor FINRA's BrokerCheck website discloses 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.

[40] Due to data limitations, we conduct Table X 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 is more sensitive to changes in regulatory oversight than the behavior of advisers.

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. Instead, the articles only include general discussions of the problem of elder financial exploitation or the new regulation. As such, publicizing 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. 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 A6.

6.4. Personal Relationships

Deep personal relationships between financial professionals and clients may have been important for the success of deputization. The policy's effect is significantly more related to the presence of investment advisers than to that of brokers. More specifically, brokers tend to have more arm's length and transactional relationships with clients that are more time specific.[41] By contrast, advisers tend to have stronger personal relationships with clients as a result of servicing fewer clients and providing services over time, such as regular financial planning sessions that document clients' circumstances and objectives.[42] 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.[43] 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. However, it may not be that advisers act because of stronger personal relationships with clients but rather because they are compensated more based on assets under management (See Table IX).

To further explore the role of personal relationships, we examine whether the policy primarily operates through advisers who are more rooted in a community and likely to have known their clients for longer. Our individual-level panel dataset of advisers allows us to measure how many months each adviser has worked in a certain county. We define *Time in County* as the number of months an adviser has been active in the county the adviser operates in as of date t. This sample for this test only includes counties with at least one

[41] See https://www.investor.gov/home/welcome-investor-gov-crs.

[42] Using Form ADV data, registered investment advisers with a proportion of employees that are brokers exceeding the full sample median service 60% more clients per employee on average in 2015.

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

deputy so that we can calculate the time variables of interest. Table XI, panel A, column (1) shows a significantly larger drop in elder financial exploitation in counties with more rooted advisers, controlling for the per capita number of advisers in each county. By contrast, panel B, column (1), shows no improvement in elder financial exploitation when brokers have been in the county longer.

There is a similar result when advisers and brokers have been in the profession longer (*Time in Profession*). These more senior financial professionals may have greater expertise or longer relationships with their clients. Panel A, column (3), attempts to tease out whether time in a specific county matters controlling for time in the profession. The coefficient on *Time in County* is negative and significant while the coefficient on *Time in Profession* becomes insignificant. An important caveat is that *Time in County* and *Time in Profession* have a correlation of 0.89.

[Insert Table XI Here]

6.5. Societal Connectedness

A client's relationships with others in the community may matter for the effectiveness of the policy. It is ex ante unclear whether deputization should work better in areas with stronger or weaker *social* relationships. On the one hand, social connections can complement the new laws and make deputization more effective. Closer-knit communities may help financial professionals detect unusual activity. Professionals in such communities are also more likely to derive utility from the increases in welfare of others because of stronger prospects of future interactions (Leider et al., 2009). On the other hand, social connections can serve as a substitute of the new regulation. Stronger social ties might suggest that others in the community have offered protection to the elderly ex ante, and therefore deputization could be less effective, because it is less needed.

We distinguish between the two hypotheses using two measures of social connectedness. First, we obtain the Social Connectedness Index from Facebook. It measures the probability that two members of a county are friends on Facebook, and follow each other's posts and activities. Table XII column (1) shows that the effect of deputization is significantly weaker in more connected counties, which is consistent with the substitution hypothesis. In other words, when people in a community are more connected, they rely less on any one particular relationship, in this case with their financial adviser.

[Insert Table XII Here]

In column (2), we use our second measure of social connectedness — the frequency of religious congregations to measure the desire for a community to interact and bond in a meaningful way (Lim and Putnam, 2010). A larger number of congregations can foster intimate relationships through frequent interactions, and may indicate a higher desire by people in a community to seek meaningful connections.[44] Supporting this assumption, the correlation between our Facebook measure of social connectedness and this measure of congregations per capita exceeds 0.7. (By contrast, the correlation between the Facebook measure and the per capita number of adherents is only 0.2.) Column (2) provides evidence consistent with a substitution effect: the effect of the new regulation is weaker in areas with a larger number of congregations per capita. More isolated elderly persons benefit marginally more from a policy that strengthens their relationship with their financial professional. By contrast, more socially-connected elderly persons benefit less from the policy.

An alternative explanation for the religious congregation result could be that religion promotes ethical behavior.[45] Consistent with this reasoning, the coefficient estimate in column (3) is positive and significant. However, in Column (4), we show that the effect of the law is significantly weaker in counties with a higher number of congregations per capita, even conditional on the number of adherents. These results are less consistent with a mechanism based on moral imperatives, but rather the substitutive role of social connections.

Because each of our proxies of interest may be correlated with other county characteristics that matter for the effect, we wish to highlight that, in all specifications, we control for variation in the effect associated with differences in the per capita number of advisers as well as variation in the effect associated with each of our controls (Yzerbyt et al., 2004).

Overall, we find evidence for a substitution effect: the role of deputies appear to be less valuable in areas where other social protections already exist.

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 socially isolated. The channel that appears to be responsible

[44] We focus on religious congregations, not other types of organizations, because it is difficult to think of any non-religious organizations in the US that are comparable in scale and scope of membership base (Lim and Putnam, 2010).

[45] 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 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).

were strong personal relationships between the elderly persons and their deputies. Egoistic incentives to preserve fees may have contributed as well. 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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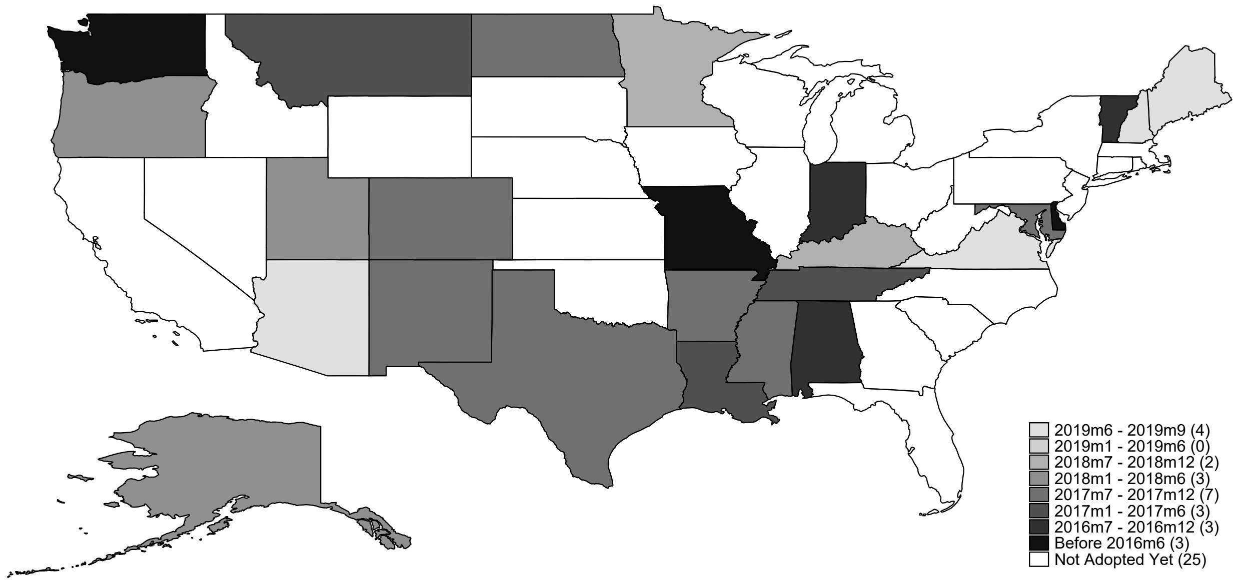
Figure I. Staggered Adoption

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 Rules 2165 and 4512.

Panel A: Model Act Adoption Date



Panel B: First Adoption Date: Model Act or FINRA Rules 2165 and 4512

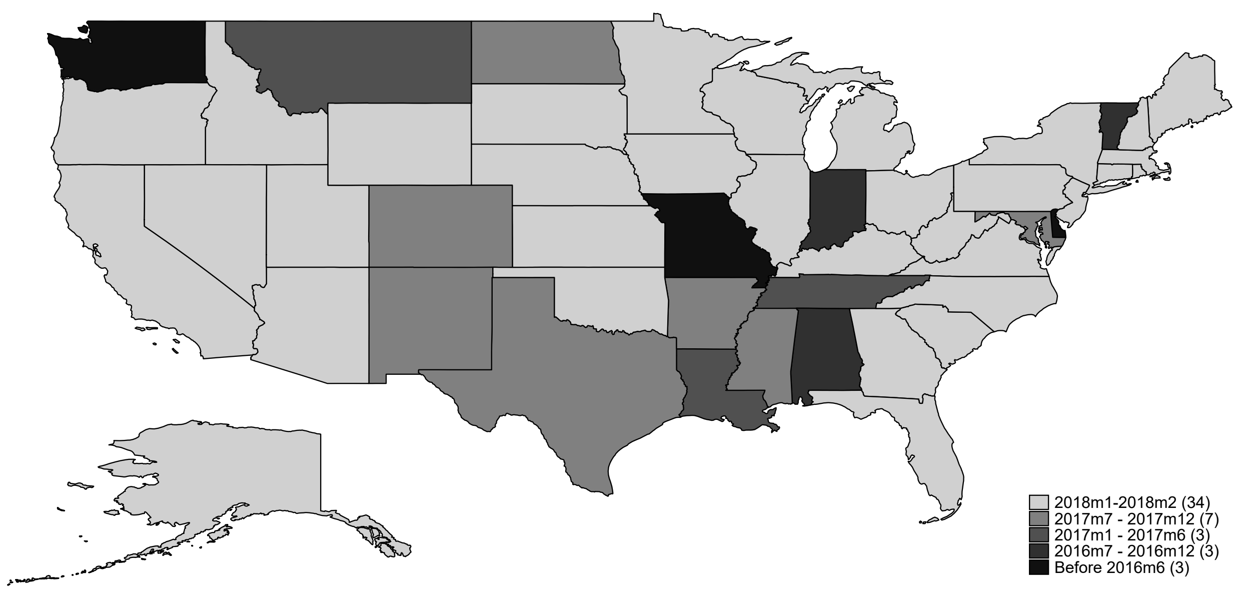


Figure II. Log Number of Elder Financial Exploitation Reports to FinCEN by Month
This figure depicts the total number of suspicious activity reports submitted to FinCEN that are flagged as related to elder financial exploitation. The counts are based on our final sample of counties, which exclude, for instance, U.S. territories and Washington D.C.

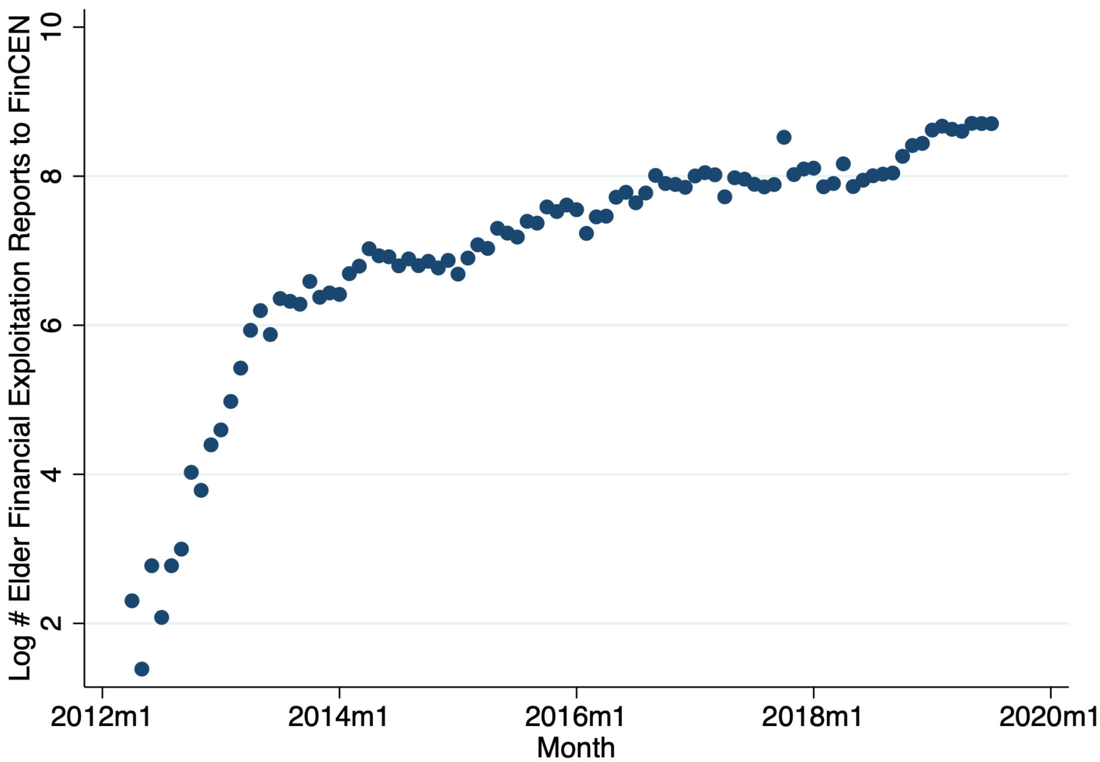


Figure III. Annual Difference-in-Difference Coefficient Plot

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 quarter 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-quarter.

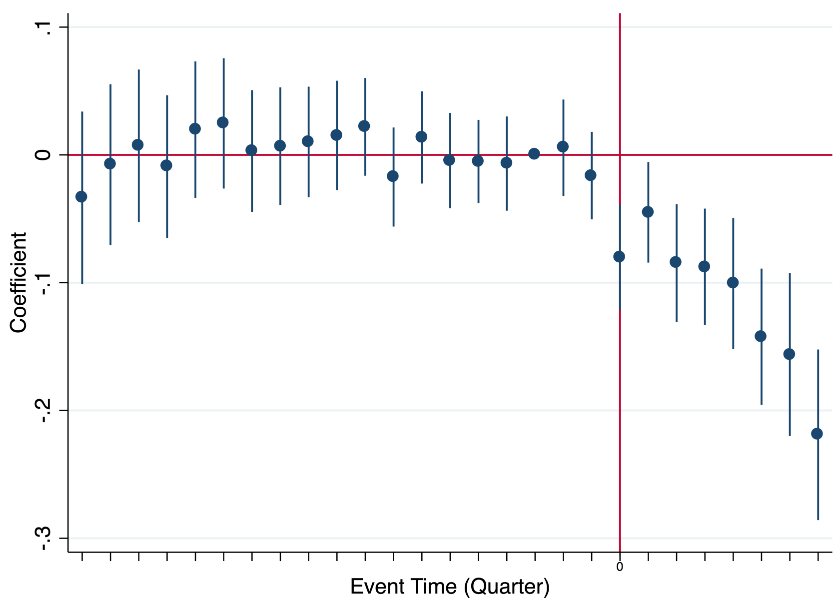
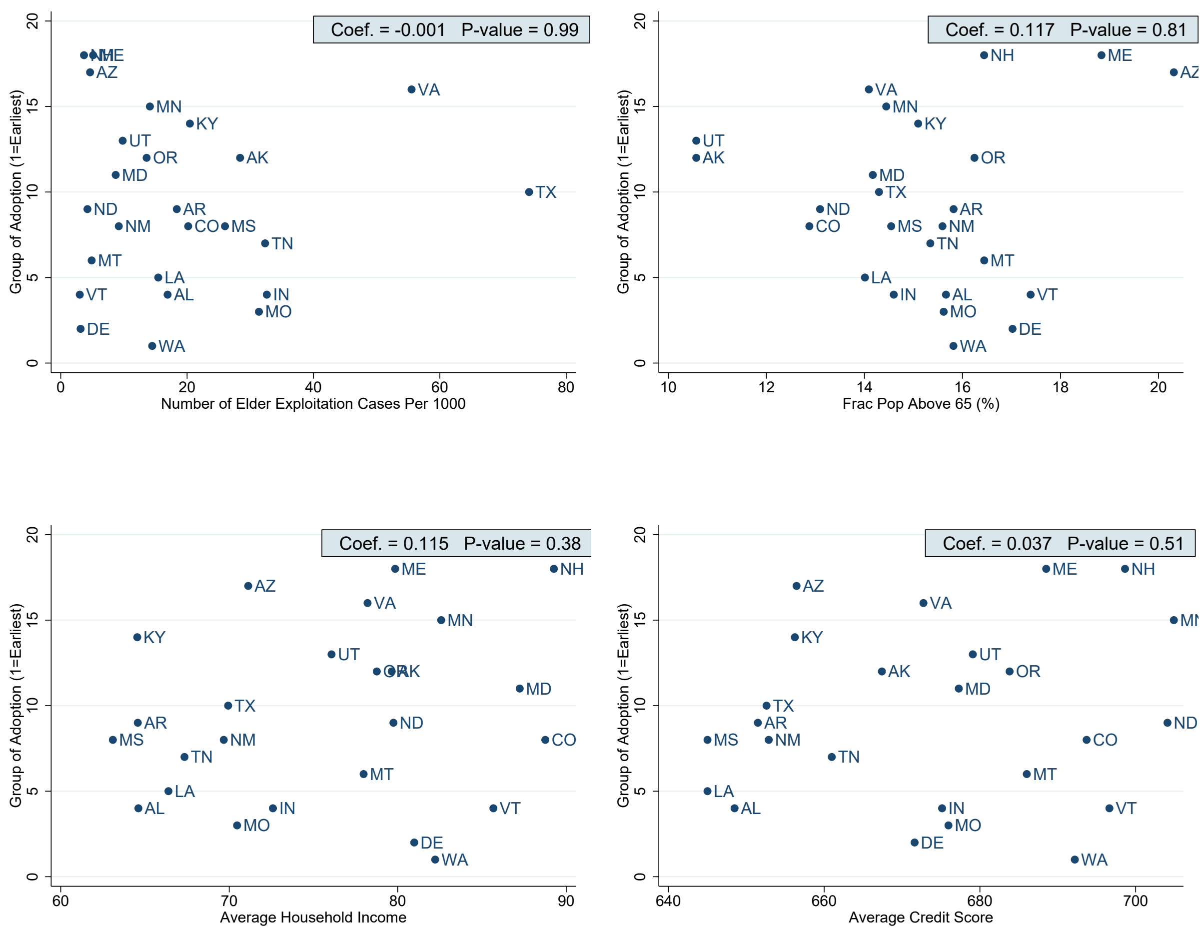
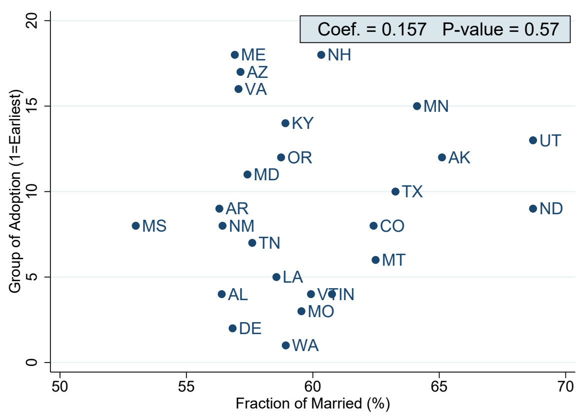


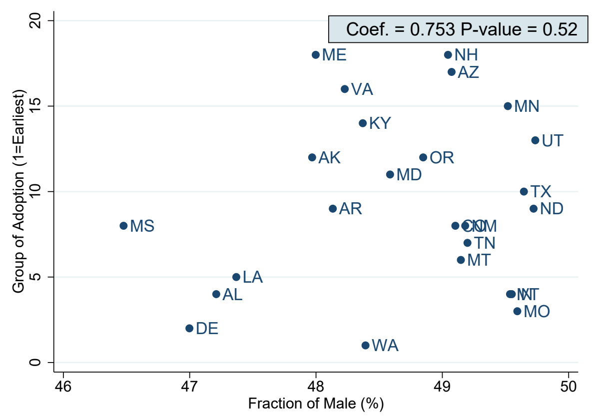
Figure IV. Do state characteristics predict the timing of adoption?

Figure 3 shows the scatter plots of the timing of the policy adoption against state characteristics for the 25 states that adopted the senior protection legislation in a staggered manner before September 2019. The corresponding regression results are reported in the Panel A of Appendix Table A2. 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 Above 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). *Log State Population* is the natural logarithm of population in a state. All variables on the x-axis are measured as of 2015, the year before the Model Act was finalized.

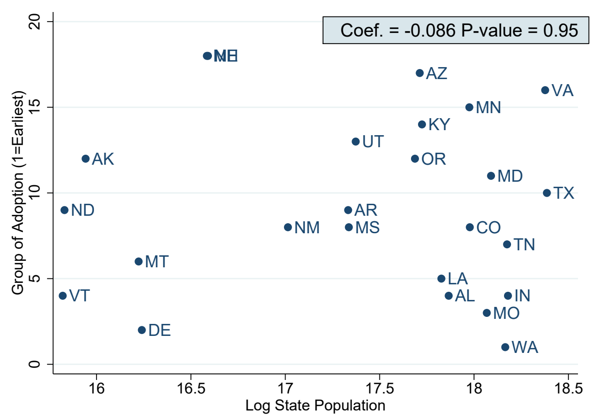




Coef. = 0.157 P-value = 0.57
Group of Adoption (1=Earliest)
Fraction of Married (%)



Coef. = 0.753 P-value = 0.52
Group of Adoption (1=Earliest)
Fraction of Male (%)



Coef. = -0.086 P-value = 0.95
Group of Adoption (1=Earliest)
Log State Population

TABLE I. Comparison Between NASAA Model Act and FINRA Rules 2165 & 4512

This table presents a detailed comparison between the institutional features of the NASAA Model Act and FINRA Rules 2165 and 4512, 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 Rules 2165 & 4512**
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 65 years of age or older or a person 18 years of age or older with mental or physical impairment
Third-Party Notification	Expressly permitted with respect to any third-party previously designated by the eligible adult.	FINRA member firms are required to make reasonable efforts to obtain the name and contact information for a trusted contact person when opening or updating a retail account. The trusted contact person is intended to be a resource for the FINRA member firm in administering the customer's account, protecting assets, and responding to possible financial exploitation.
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 II. 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 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 III. Summary Statistics

Panel A 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. *Religious Adherents Per 1000* is the number of individuals with and without an affiliation to a congregation. *Religious Congregation per 1000* is the number of religious congregations per 1000 individuals. Panel B reports characteristics of suspicious activity reports related to elder financial exploitation submitted to the U.S. Treasury's FinCEN database.

Panel A: County-Month Summary Statistics

Variables	(1) Mean	(2) SD	(3) p10	(4) p50	(5) p90	(6) N
Elder Financial Exploitation Cases	1.1	6.2	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

Panel B: FinCEN Elder Financial Exploitation SARS Statistics

Instrument		Product	
U.S. Currency	35.9%	Debit Card	37.9%
Funds Transfer	28.7%	Deposit Account	16.4%
Personal/Business Check	18.4%	Credit Card	11.9%
Bank/Cashier's Check	7.0%	Other	33.8%
Other	9.9%		
Regulator		**Industry**	
OCC	48.3%	Depository Institution	75.5%
IRS	21.2%	Money Services Business	20.8%
FRB	17.1%	Securities/Futures	2.8%
FDIC	8.9%	Other	0.9%
Other	4.5%		

TABLE IV. 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 III's legend. Standard errors, double-clustered by state and month, 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)	(5)	(6)
Post	-0.063	-0.059**	-0.059**	-0.038	-0.053**	-0.042**
	(0.066)	(0.023)	(0.023)	(0.028)	(0.022)	(0.019)
Log Pop Above 65				0.311***	0.329***	2.168***
				(0.028)	(0.028)	(0.403)
Vantage Score				-0.063**	-0.041*	0.087**
				(0.024)	(0.021)	(0.037)
Fraction of Subprime				-0.007	-0.006	-0.017
				(0.025)	(0.018)	(0.014)
Fraction of Low Income				0.061***	0.050***	0.015
				(0.021)	(0.015)	(0.012)
Average Age				-0.076***	-0.079***	-0.145***
				(0.017)	(0.015)	(0.031)
Fraction of Male				0.004	-0.002	0.003
				(0.004)	(0.004)	(0.004)
Married				-0.012	-0.027***	0.020*
				(0.009)	(0.006)	(0.011)
Household Income				0.140***	0.117***	0.137***
				(0.030)	(0.025)	(0.041)
Household Debt-to-Income Ratio				-0.047***	-0.058***	-0.032**
				(0.011)	(0.011)	(0.012)
Bachelor or Higher				0.031	0.016	0.102***
				(0.020)	(0.020)	(0.028)
Constant	0.291***	0.290***	0.290***	0.284***	0.288***	0.284***
	(0.036)	(0.006)	(0.006)	(0.015)	(0.006)	(0.005)
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	No	Yes	No
County FE	No	No	Yes	No	No	Yes
Adjusted R^2	0.07	0.16	0.50	0.37	0.39	0.51
# Counties	2557	2557	2557	2557	2557	2557
Observations	225016	225016	225016	225016	225016	225016

Panel B:	I(Elder Financial Exploitation Cases)>0					
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.034	-0.025***	-0.025***	-0.023**	-0.023**	-0.017**
	(0.034)	(0.009)	(0.009)	(0.011)	(0.009)	(0.008)
Log Pop Above 65				0.162***	0.171***	1.306***
				(0.010)	(0.010)	(0.149)
Vantage Score				-0.027**	-0.014	0.018
				(0.010)	(0.009)	(0.013)
Fraction of Subprime				-0.005	-0.004	-0.003
				(0.010)	(0.008)	(0.006)
Fraction of Low Income				0.019***	0.014***	0.004
				(0.007)	(0.005)	(0.004)
Average Age				-0.025***	-0.025***	-0.039***
				(0.004)	(0.003)	(0.009)
Fraction of Male				0.000	-0.001	0.001
				(0.002)	(0.002)	(0.002)
Married				-0.004	-0.008***	0.010**
				(0.004)	(0.003)	(0.005)
Household Income				0.042***	0.026***	0.020*
				(0.008)	(0.008)	(0.011)
Household Debt-to-Income Ratio				-0.010***	-0.014***	-0.012**
				(0.003)	(0.003)	(0.005)
Bachelor or Higher				0.025***	0.021***	0.040***
				(0.007)	(0.006)	(0.012)
Constant	0.187***	0.185***	0.185***	0.184***	0.184***	0.182***
	(0.018)	(0.002)	(0.002)	(0.006)	(0.002)	(0.002)
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	No	Yes	No
County FE	No	No	Yes	No	No	Yes
Adjusted R^2	0.07	0.13	0.36	0.31	0.32	0.37
# Counties	2557	2557	2557	2557	2557	2557
Observations	225016	225016	225016	225016	225016	225016

TABLE V. Effects of Deputization on a Matched Sample of Counties

In this table, we perform the difference-in-difference analysis in Table IV 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 a bachelor's degree 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 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 and B. The outcome in Panel A is the natural logarithm of one plus the number of elder financial exploitation cases. The outcome in Panel B is an indicator that takes a value of one if a county has above zero cases in a month. We also present the covariate balance tests on the matched sample of counties in Panels C-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 Rules 2165 and 4512. Standard errors, double-clustered by state and month, 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)
	25^{th} Percentile	50^{th} Percentile	75^{th} Percentile
Post	-0.050*	-0.055*	-0.058**
	(0.029)	(0.030)	(0.027)
Pair FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Adjusted R^2	0.39	0.41	0.44
# Counties	1918	1918	1918
Observations	112464	224752	337568

Panel B:	I(Elder Financial Exploitation Cases)>0		
	(1)	(2)	(3)
	25^{th} Percentile	50^{th} Percentile	75^{th} Percentile
Post	-0.021*	-0.023**	-0.027**
	(0.010)	(0.011)	(0.010)
Pair FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Adjusted R^2	0.30	0.31	0.33
# Counties	1918	1918	1918
Observations	112464	224752	337568

Panel C: Covariate Balance: 25^{th} Percentile Threshold

	Treat = 0		Treat = 1			
	Mean	SD	Mean	SD	P-value	Std. Diff.
Log Population Above 65	0.30	(0.72)	0.29	(0.73)	(0.86)	-0.01
Vantage Score	-0.31	(0.71)	-0.32	(0.70)	(0.78)	-0.01
Fraction of Subprime	0.27	(0.71)	0.28	(0.69)	(0.83)	0.01
Fraction of Low Income	0.33	(0.74)	0.32	(0.74)	(0.89)	-0.01
Average Age	-0.09	(0.62)	-0.13	(0.64)	(0.34)	-0.04
Fraction of Male	0.00	(0.58)	0.02	(0.56)	(0.59)	0.02
Fraction of Married	-0.08	(0.66)	-0.07	(0.66)	(0.86)	0.01
Household Income	-0.32	(0.65)	-0.30	(0.64)	(0.58)	0.02
Household Debt-to-Income Ratio	-0.00	(0.65)	0.02	(0.64)	(0.54)	0.02
Fraction with Bachelor or Higher	-0.25	(0.75)	-0.25	(0.76)	(0.90)	0.00
Observations	639		639			

Panel D: Covariate Balance: 50^{th} Percentile Threshold

	Treat = 0		Treat = 1			
	Mean	SD	Mean	SD	P-value	Std. Diff.
Log Population Above 65	0.22	(0.77)	0.22	(0.78)	(0.91)	-0.00
Vantage Score	-0.25	(0.82)	-0.27	(0.79)	(0.55)	-0.02
Fraction of Subprime	0.23	(0.82)	0.24	(0.79)	(0.76)	0.01
Fraction of Low Income	0.26	(0.83)	0.27	(0.82)	(0.83)	0.01
Average Age	-0.07	(0.71)	-0.10	(0.72)	(0.40)	-0.02
Fraction of Male	-0.02	(0.67)	-0.02	(0.66)	(0.94)	0.00
Fraction of Married	-0.03	(0.72)	-0.03	(0.71)	(0.99)	0.00
Household Income	-0.25	(0.74)	-0.25	(0.73)	(0.79)	0.01
Household Debt-to-Income Ratio	-0.00	(0.74)	0.02	(0.72)	(0.49)	0.02
Fraction with Bachelor or Higher	-0.21	(0.84)	-0.22	(0.84)	(0.84)	-0.01
Observations	1,277		1,277			

Panel E: Covariate Balance: 75^{th} Percentile Threshold

	Treat = 0		Treat = 1			
	Mean	SD	Mean	SD	P-value	Std. Diff.
Log Population Above 65	0.16	(0.85)	0.16	(0.82)	(0.86)	0.00
Vantage Score	-0.17	(0.90)	-0.19	(0.85)	(0.35)	-0.02
Fraction of Subprime	0.14	(0.89)	0.17	(0.84)	(0.41)	0.02
Fraction of Low Income	0.19	(0.90)	0.19	(0.89)	(0.97)	0.00
Average Age	-0.05	(0.80)	-0.07	(0.79)	(0.43)	-0.02
Fraction of Male	-0.01	(0.77)	-0.00	(0.76)	(0.95)	0.00
Fraction of Married	-0.01	(0.80)	0.01	(0.77)	(0.47)	0.02
Household Income	-0.17	(0.82)	-0.17	(0.82)	(0.97)	-0.00
Household Debt-to-Income Ratio	-0.02	(0.82)	0.00	(0.80)	(0.35)	0.02
Fraction with Bachelor or Higher	-0.16	(0.90)	-0.16	(0.90)	(0.92)	-0.00
Observations	1,918		1,918			

TABLE VI. Effect by SARs Product and Instrument

This table presents difference-in-differences estimates of the effect of deputizing financial professionals on elder financial exploitation by the type of financial product and instrument involved. *Post* is an indicator variable that equals to one after a state adopts the Model Act. A detailed description of the control variables can be found in Table IV legend. Standard errors, double-clustered by state and month, are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: By Product

	Ln(1+Elder Financial Exploitation Cases)						
	Debit Card	Credit Card	Deposit Account	HELOC	Insurance	Mutual Fund	Prepaid Access
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post	-0.042**	-0.013	0.013	0.000	-0.000	0.001	-0.002
	(0.016)	(0.009)	(0.014)	(0.000)	(0.001)	(0.001)	(0.002)
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.42	0.33	0.26	0.02	0.11	0.09	0.12
Observations	225016	225016	225016	225016	225016	225016	225016

Panel B: By Instrument

	Ln(1+Elder Financial Exploitation Cases)					
	Fund Transfer	Bank Cashier Check	Personal Check	U.S. Currency	Money Orders	Foreign Currency
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.028**	-0.005	-0.018*	-0.024**	-0.001	-0.005
	(0.013)	(0.004)	(0.009)	(0.011)	(0.002)	(0.004)
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.47	0.27	0.42	0.44	0.13	0.11
Observations	225016	225016	225016	225016	225016	225016

TABLE VII. The Deputies

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 Rules 2165 and 4512. In Panel A, *Per Capita Investment Advisers (Brokers)* is a county's per capita number of investment advisers (brokers). *% Dual-Registered Advisers* is a county's fraction of investment advisers dual-registered as brokers. In Panel B, the count of elder financial exploitation is broken down by type of reporting institution. Note that depository institutions include bank holding companies that may contain divisions providing investment advisery and broker-dealer services. All regressions include 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. All regressions also include county and year-month fixed effects. Each control is interacted with *Post* (Yzerbyt et al., 2004). Additionally, each variable of interest interacted with *Post* is interacted with all explanatory variables and the year-month fixed effects. Standard errors, double-clustered by state and month, are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Effect by Financial Professional Type

	Ln(1+Elder Financial Exploitation Cases)			
	(1)	(2)	(3)	(4)
Post	-0.045***	-0.039**	-0.044**	-0.034**
	(0.016)	(0.016)	(0.017)	(0.017)
Post × Per Capita Investment Advisers	-0.040**		-0.040**	-0.124***
	(0.018)		(0.018)	(0.039)
Post × Per Capita Brokers		-0.004		0.137**
		(0.024)		(0.056)
Post × % Dual-Registered Advisers			0.019*	
			(0.010)	
Interacted Controls	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.59	0.59	0.59	0.59
# Counties	2557	2557	2557	2557
Observations	225016	225016	225016	225016

Panel B: Effect by Reporting Institution

	Ln(1+Elder Financial Exploitation Cases)		
	Depository Institution	Money Services Business	Securities
	(1)	(2)	(3)
Post	-0.039**	-0.019	0.002
	(0.017)	(0.014)	(0.002)
Year-Month FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Adjusted R^2	0.48	0.28	0.29
# Counties	2557	2557	2557
Observations	225016	225016	225016

TABLE VIII. Welfare Effects

This table presents difference-in-differences estimates of the effect of deputization on senior financial outcomes. The sample includes annual observations for 2,787,979 people of age 18 or greater from 2010 to 2019. *I(Bankruptcy Event in Year t)×100* is an indicator variable that equals to 100 if an individual experiences at least one bankruptcy event in year t. The unconditional frequency of bankruptcy is 46 basis points. *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 (t-1)* is the individual's credit score at the end of the prior year. All columns include year fixed and census tract fixed effects. Column (3) includes fixed effects for individuals. Standard errors, double-clustered by state and year, are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	I(Bankruptcy Event in Year t)×100			
	(1)	(2)	(3)	(4)
Post	0.079**	0.079**		
	(0.025)	(0.025)		
Post × Age ≥ 65	-0.110***	-0.089***	-0.102***	-0.081***
	(0.028)	(0.023)	(0.028)	(0.023)
Post × Age ≥ 80		-0.054**		-0.057**
		(0.018)		(0.019)
Age ≥ 65	-0.067**	-0.078***	-0.066**	-0.078***
	(0.022)	(0.021)	(0.023)	(0.022)
Age ≥ 80		0.003		0.007
		(0.016)		(0.015)
Vantage Score ($t-1$)	-0.983***	-0.984***	-0.980***	-0.981***
	(0.143)	(0.143)	(0.142)	(0.142)
Vantage Score $(t-1)^2$	0.421***	0.420***	0.425***	0.425***
	(0.071)	(0.071)	(0.072)	(0.072)
Constant	0.065	0.068	0.080	0.082
	(0.071)	(0.071)	(0.069)	(0.069)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No
Tract x Year FE	No	No	Yes	Yes
Adjusted R^2	0.01	0.01	0.01	0.01
# Individuals	2787979	2787979	2787979	2787979
Observations	23511601	23511601	23511601	23511601

TABLE IX. Financial Incentives

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 2,221 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 Rules 2165 and 4512. *AUM-Per-Client* is the average AUM per client in a county, where AUM per client is determined at the firm level. *Compensation Hourly* is the proportion of advisers associated with firms that charge an hourly fee for services. *Compensation Commissions* is the proportion of advisers associated with firms that charge commissions. *Compensation Fixed Fees* is the proportion of advisers associated with firms that charge fixed fees. All regressions include 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. All regressions also include county and year-month fixed effects. Each control is interacted with *Post* (Yzerbyt et al., 2004). Additionally, each variable of interest interacted with *Post* is interacted with all explanatory variables and the year-month fixed effects. Standard errors, double-clustered by state and month, 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	-0.059***	-0.043**	-0.042**	-0.042**	-0.060***
	(0.020)	(0.018)	(0.018)	(0.019)	(0.021)
Post × Per Capita Investment Advisers	-0.008	-0.038**	-0.036**	-0.035*	-0.009
	(0.015)	(0.017)	(0.018)	(0.017)	(0.016)
Post × AUM-Per-Client	-0.101***				-0.097***
	(0.027)				(0.027)
Post × Compensation Hourly		-0.004			0.017
		(0.011)			(0.019)
Post × Compensation Commissions			-0.013		0.001
			(0.012)		(0.012)
Post × Compensation Fixed Fees				-0.018	-0.025
				(0.014)	(0.023)
Interacted Controls	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.60	0.59	0.59	0.59	0.60
# Counties	2221	2221	2221	2221	2221
Observations	195448	195800	195800	195800	195448

TABLE X. 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 Rules 2165 and 4512. All regressions include county and year-month fixed effects. In columns with interacted terms, the year-month fixed effects are interacted with the high/low indicator to control for possible differential trends across counties in the high and low groups. 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, double-clustered by state and month, 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	-0.00005
	(0.00033)	(0.00175)	(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
Observations	225016	225016	225016

TABLE XI. 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 Rules 2165 and 4512. *Time in County* is the average number of months advisers or brokers have operated in their current county. *Time in Profession* is the average number of months advisers or brokers have been in the profession. *Per Capita Investment Advisers (Brokers)* is a county's per capita number of investment advisers (brokers). All regressions include 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. All regressions also include county and year-month fixed effects. Each control is interacted with *Post* (Yzerbyt et al., 2004). Additionally, each variable of interest interacted with *Post* is interacted with all explanatory variables and the year-month fixed effects. Standard errors, double-clustered by state and month, 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)
Post	-0.045**	-0.044**	-0.042**
	(0.017)	(0.017)	(0.018)
Post × Per Capita Investment Advisers	-0.035**	-0.037**	-0.034*
	(0.017)	(0.017)	(0.017)
Post × Time in County	-0.022**		-0.041**
	(0.011)		(0.018)
Post × Time in Profession		-0.023*	0.016
		(0.013)	(0.021)
Controls	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Adjusted R^2	0.59	0.59	0.59
# Counties	2244	2244	2244
Observations	197472	197472	197472

Panel B: Brokers			
	Ln(1+Elder Financial Exploitation Cases)		
	(1)	(2)	(3)
Post	-0.039**	-0.040**	-0.040**
	(0.017)	(0.018)	(0.017)
Post × Per Capita Brokers	-0.002	-0.007	-0.005
	(0.024)	(0.025)	(0.024)
Post × Time in County	0.015		0.003
	(0.014)		(0.014)
Post × Time in Profession		0.016	0.015
		(0.012)	(0.010)
Controls	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Adjusted R^2	0.59	0.59	0.59
# Counties	2398	2398	2398
Observations	211024	211024	211024

TABLE XII. Social Connectedness

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 Rules 2165 and 4512. *Social Connectedness Index* is a county's Social Connectedness Index measured using Facebook friendship connections. *Adherents (Congregations) Per 1000* is a county's number of religious adherents (congregations) per thousand population. All regressions include time-varying county control, 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. All regressions also include county and year-month fixed effects. Each control is interacted with *Post* (Yzerbyt et al., 2004). Additionally, each variable of interest interacted with *Post* is interacted with all explanatory variables and the year-month fixed effects. Standard errors, double-clustered by state and month, 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	-0.085***	-0.086***	-0.044*	-0.091***
	(0.025)	(0.022)	(0.023)	(0.022)
Post × Per Capita Investment Advisers	-0.115***	-0.100***	-0.165***	-0.095***
	(0.026)	(0.024)	(0.033)	(0.024)
Post × Social Connectedness Index	0.093**			
	(0.035)			
Post × Congregations Per 1000		0.115***		0.114***
		(0.024)		(0.029)
Post × Adherents Per 1000			0.050***	-0.012
			(0.015)	(0.019)
Interacted Controls	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.57	0.58	0.56	0.58
# Counties	2557	2557	2557	2557
Observations	225016	225016	225016	225016

Appendix A. Robustness

Figure A1. Main Effect Dropping Each State

This figure shows the distribution of the estimated policy effect in Table IV Column (6) 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.

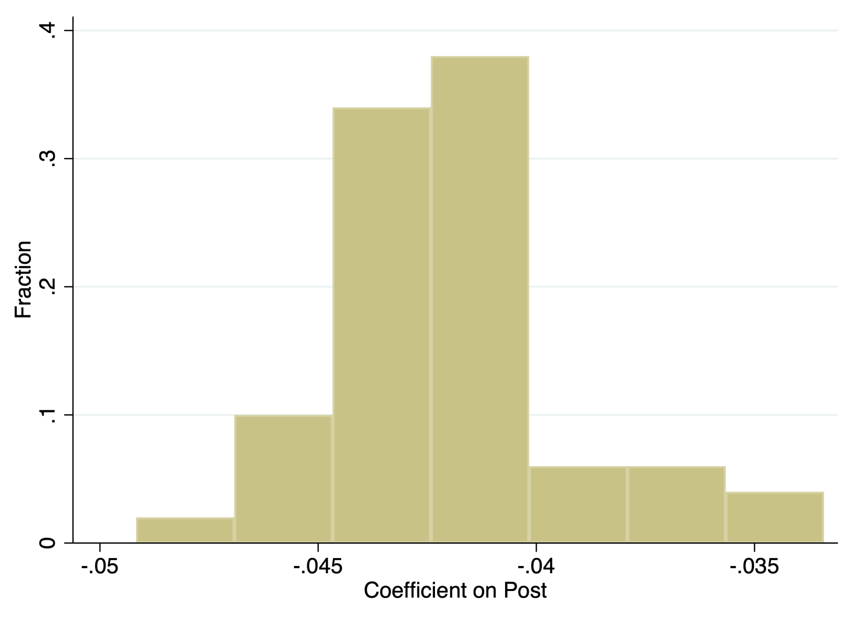


Figure A2. Main Effect Randomizing Post for Each State 100 Times

This figure shows the distribution of the estimated effect and its t-statistic as in Table IV Column (6) when randomizing *Post* for each state. We repeat the randomization 100 times. The figure shows that the result is unusual and not a mechanical feature of the data or empirical specification.

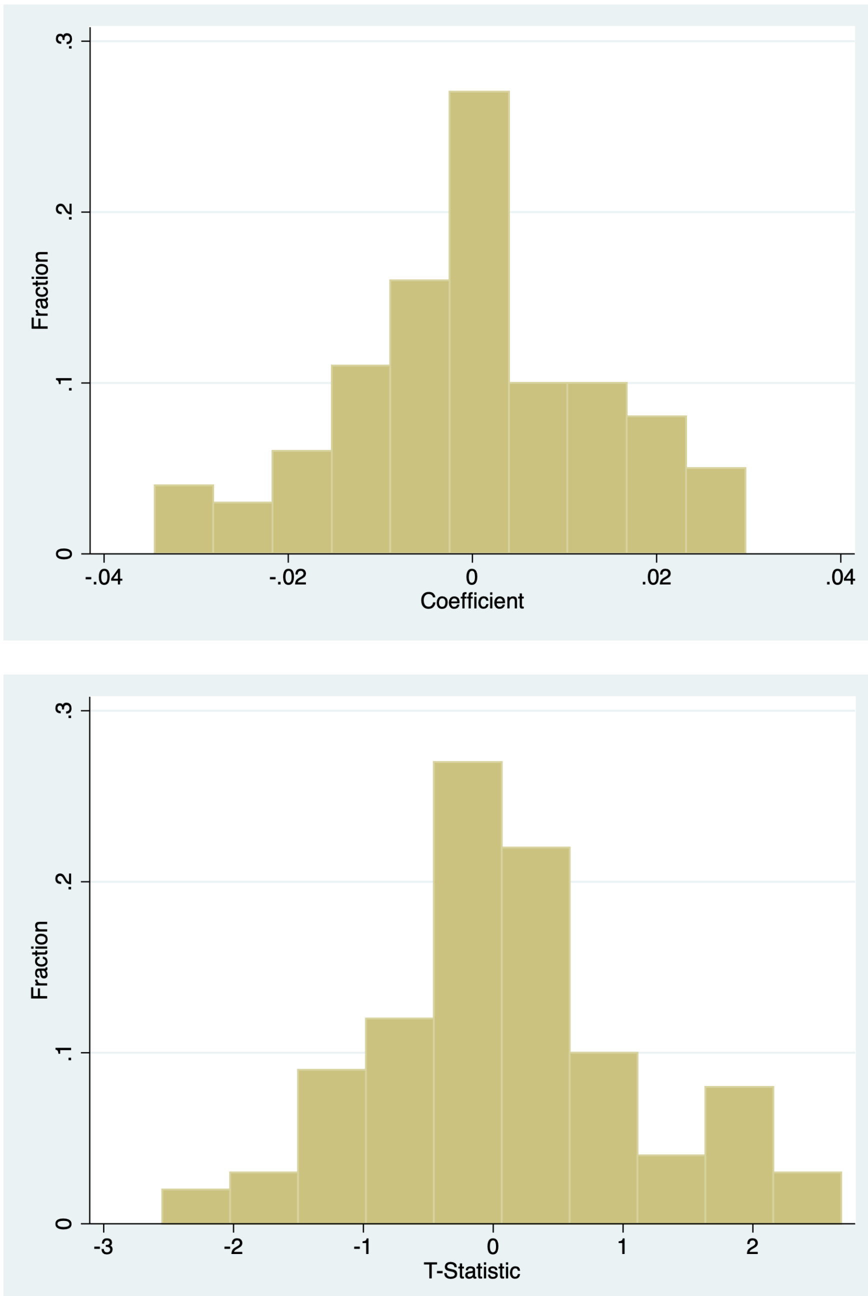


TABLE A1. Correlations

Ln(1+Elder Financial Exploitation Cases)	1.0																					
Log Population Above 65	0.5	1.0																				
Vantage Score	0.1	0.1	1.0																			
Fraction of Subprime	-0.1	-0.1	-1.0	1.0																		
Fraction of Low Income	-0.1	-0.2	-0.8	0.8	1.0																	
Average Age	-0.1	-0.2	0.3	-0.3	-0.1	1.0																
Fraction of Male	-0.1	-0.1	0.2	-0.2	-0.1	0.1	1.0															
Married	-0.2	-0.4	0.4	-0.3	-0.4	0.1	0.2	1.0														
Household Income	0.3	0.3	0.8	-0.8	-0.8	0.2	0.1	0.3	1.0													
Household Debt-to-Income Ratio	0.1	0.2	-0.1	0.1	-0.2	-0.4	0.0	0.2	0.1	1.0												
Bachelor or Higher	0.3	0.5	0.5	-0.5	-0.7	-0.2	-0.0	-0.0	0.8	0.2	1.0											
Income Larger 200k	0.3	0.5	0.4	-0.4	-0.6	-0.2	-0.0	0.0	0.7	0.2	0.8	1.0										
Mean Retirement Income	0.3	0.4	0.2	-0.2	-0.4	-0.1	-0.0	-0.1	0.5	0.2	0.6	0.6	1.0									
Vantage Score	0.1	0.1	1.0	-1.0	-0.8	0.3	0.2	0.4	0.8	-0.1	0.5	0.4	0.2	1.0								
Married	-0.2	-0.4	0.4	-0.3	-0.4	0.1	0.2	1.0	0.3	0.2	-0.0	0.0	-0.1	0.4	1.0							
Female	0.2	0.3	-0.3	0.3	0.3	-0.2	-0.2	-0.5	-0.2	0.0	0.0	0.0	-0.1	-0.3	-0.5	1.0						
Pop Above 85	0.0	-0.0	0.4	-0.4	-0.1	0.1	0.0	-0.0	0.2	-0.2	0.2	0.1	-0.2	0.4	-0.0	0.4	1.0					
Bachelor or Higher	0.3	0.5	0.5	-0.5	-0.7	-0.2	-0.0	-0.0	0.8	0.2	1.0	0.8	0.6	0.5	-0.0	0.0	0.2	1.0				
Pop White	-0.2	-0.1	0.6	-0.5	-0.4	0.3	0.3	0.4	0.3	-0.1	0.0	-0.0	-0.1	0.6	0.4	-0.3	0.2	0.0	1.0			
Asian	0.4	0.5	0.1	-0.1	-0.2	-0.3	-0.1	-0.2	0.4	0.2	0.5	0.6	0.4	0.1	-0.2	0.1	-0.0	0.5	-0.3	1.0		
Black	0.1	0.1	-0.6	0.5	0.4	-0.2	-0.3	-0.5	-0.3	0.1	-0.1	-0.1	0.0	-0.6	-0.5	0.4	-0.2	-0.1	-0.9	0.1	1.0	
Hispanic	0.1	0.1	-0.2	0.2	0.1	-0.2	0.0	0.0	-0.1	0.2	-0.0	0.1	0.1	-0.2	0.0	-0.0	-0.0	-0.0	0.0	0.2	-0.1	1.0

TABLE A2. 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. In Panel A, we limit the analysis to the 25 states that have adopted the Model Act by 2019, and examine whether the timing of adoption is related to state characteristics. 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. In Panel B, we examine whether the extensive margin of adoption (i.e. *whether* a state adopts the Model Act by 2019) is related to state characteristics. The outcome variable, *Adoption Dummy*, is an indicator variable that takes a value of one if a state adopts the Model Act by 2019. *Number of Elder Exploitation Cases Per 1000* measures the number of elder exploitation cases per 1,000 population that are age 65 and above. *Fraction of Population 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). *Log State Population* is the natural logarithm of state population. All variables on the x-axis are measured as of 2015, the year before the Model Act was finalized.

Panel A: Group of Adoption (1 = Earliest)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of Elder Exploitation Cases Per 1000	-0.001						
	(0.063)						
Fraction of Population 65+		0.117					
		(0.494)					
Average Household Income			0.115				
			(0.129)				
Average Credit Score				0.037			
				(0.055)			
Fraction of Married					0.157		
					(0.273)		
Fraction of Male						0.753	
						(1.140)	
Log State Population							-0.086
							(1.257)
R^2	0.00	0.00	0.03	0.02	0.01	0.02	0.00
# States	25	25	25	25	25	25	25

Panel B: Adoption Dummy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of Elder Exploitation Cases Per 1000	0.002						
	(0.005)						
Fraction of Population 65+		-0.056*					
		(0.033)					
Average Household Income			-0.012				
			(0.008)				
Average Credit Score				-0.006			
				(0.004)			
Fraction of Married					0.011		
					(0.018)		
Fraction of Male						-0.046	
						(0.071)	
Log State Population							-0.097
							(0.074)
R^2	0.00	0.06	0.04	0.04	0.01	0.01	0.03
# States	50	50	50	50	50	50	50

TABLE A3. Effects of Deputization on Elder Financial Exploitation: Pre-FINRA Rules 2165 and 4512

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 FINRA Rules 2165 and 4512. *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 IV legend. Standard errors, double-clustered by state and month, 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	-0.063	-0.042	-0.064**	-0.053**
	(0.066)	(0.032)	(0.029)	(0.026)
Log Pop Above 65		0.261***	0.276***	2.316***
		(0.026)	(0.026)	(0.364)
Vantage Score		-0.049**	-0.032	0.088**
		(0.022)	(0.020)	(0.034)
Fraction of Subprime		-0.003	0.000	-0.014
		(0.022)	(0.016)	(0.014)
Fraction of Low Income		0.058***	0.051***	0.022*
		(0.018)	(0.013)	(0.012)
Average Age		-0.061***	-0.063***	-0.110***
		(0.015)	(0.013)	(0.026)
Fraction of Male		0.004	-0.001	0.006
		(0.004)	(0.003)	(0.004)
Fraction of Married		-0.005	-0.019***	0.028**
		(0.007)	(0.006)	(0.011)
Household Income		0.119***	0.104***	0.092***
		(0.028)	(0.024)	(0.034)
Household Debt-to-Income Ratio		-0.038***	-0.047***	-0.025**
		(0.010)	(0.009)	(0.010)
Fraction with Bachelor or Higher		0.029*	0.015	0.084***
		(0.017)	(0.017)	(0.026)
Constant	0.227***	0.230***	0.230***	0.265***
	(0.024)	(0.011)	(0.002)	(0.005)
Year-Month FE	Yes	Yes	Yes	Yes
State FE	No	No	Yes	No
County FE	No	No	No	Yes
Adjusted R^2	0.07	0.34	0.36	0.49
# Counties	2557	2557	2557	2557
Observations	178990	178990	178990	178990

TABLE A4. Placebo

This table presents difference-in-differences estimates of the effect of the deputizing financial professionals on placebo outcomes. In Column (1), the placebo outcome is "Ln(1+Insider Trading)", which is the number of FinCEN suspicious activity reports related to insider trading in a county-month. In Column (2), the placebo outcome is "Ln(1+Terrorism Financing)", which is the number of FinCEN suspicious activity reports related to terrorism. The sample only includes months from 2014 to July 2019, because at the time of acquiring the data FinCEN only provides data starting in 2014. *Post* is an indicator variable that equals to one after a state adopts the Model Act. A detailed description of the control variables can be found in Table IV legend. Standard errors, double-clustered by state and month, are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Ln(1+Insider Trading)	**Ln(1+Terrorism Financing)**
	(1)	(2)
Post	-0.006	-0.002
	(0.006)	(0.002)
Log Population Above 65	0.108	-0.076
	(0.120)	(0.051)
Vantage Score	0.026***	0.008***
	(0.009)	(0.003)
Fraction of Subprime	-0.003	-0.001
	(0.004)	(0.001)
Fraction of Low Income	0.003	0.001
	(0.003)	(0.001)
Average Age	-0.033***	-0.011***
	(0.009)	(0.003)
Fraction of Male	0.001	0.000
	(0.001)	(0.000)
Fraction of Married	0.005*	0.001
	(0.003)	(0.001)
Household Income	0.032***	0.014***
	(0.012)	(0.005)
Household Debt-to-Income Ratio	-0.006**	-0.004***
	(0.003)	(0.001)
Fraction with Bachelor or Higher	0.010*	0.001
	(0.005)	(0.002)
Constant	0.033***	0.010***
	(0.002)	(0.000)
Year-Month FE	Yes	Yes
County FE	Yes	Yes
Adjusted R^2	0.26	0.41
# Counties	2557	2557
Observations	225016	225016

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.

Using the Goodman-Bacon (2018) decomposition, we find that our estimator is mainly driven by variations within the timing group.[46] As shown in Table A5, the 2x2 estimators within the timing group can be divided into two components. The first component is "Earlier Treated vs Later Control", which compares the states that adopted earlier to the states that have not yet adopted the policy. The average coefficient estimate derived from this source of variation is -0.05 and has a weight of 67%. The second component is "Later Treated vs Earlier Control", which compares the states that adopted later to the states that have already adopted the policy. The average coefficient estimate derived from this source of variation is 0.015 and has a weight of 24.9%. This coefficient estimate is slightly positive, because of the non-immediate policy effect. In other words, when the earlier treated states serve as controls, they are still reacting to the policy, biasing the overall estimate to zero. The estimators derived from differences between the timing group and the already-treated group receives a weight of only 8.2%, and has an average coefficient estimate of -0.133. In the current specification, we do not have any never-treated states in the data, so that source of variation does not contribute to our estimates.

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

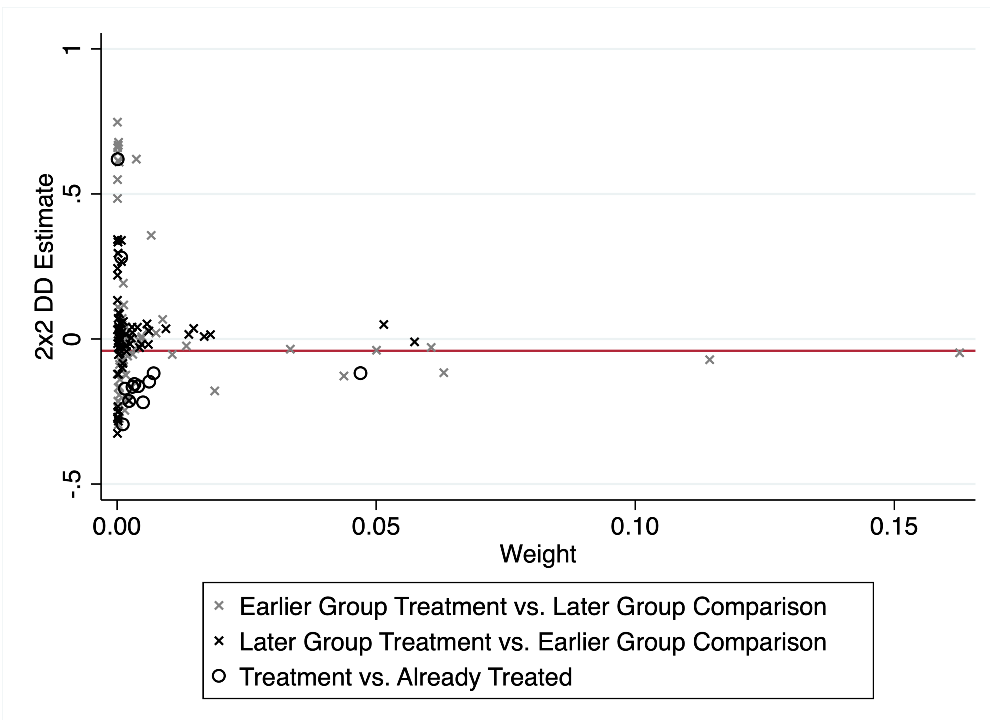
TABLE A5. Goodman-Bacon Decomposition

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. The empirical specification is the same with the specification used in Table IV Panel A Column (4).

Variation	**Beta**	**Weight**
Earlier Treated vs Later Control	-0.050	0.670
Later Treated vs Earlier Control	0.015	0.249
Treated vs Already Treated	-0.133	0.082

Figure A3. 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 A5.



Appendix C. Factiva Searches

TABLE A6. 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