Deputization

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Abstract

Deputization is a permissive policy that asks agents to help screen for dangerous activities without providing explicit incentives. To assess its efficacy, we exploit the staggered adoption of recent laws that deputized financial professionals to help fight elder financial abuse — a widespread and pernicious problem that is hard to police. We find that deputization led to a 6%-9% decrease in elder financial abuse. Investment advisers may be more effective deputies than brokers, and existing safeguards curbed the benefits of deputization.

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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 (egoistic) incentives or intrinsic motivations (e.g., 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 calling upon individuals to report suspicious activities at airports, to identify illegal immigration (Lin, 2009), and to stop 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. We identify such an opportunity in an important setting - elder financial exploitation. Specifically, 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

[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. See https://files.consumerfinance.gov/f/documents/cfpb_suspicious-activity-reports-elder-financial-exploitation_report.pdf. DeLiema et al. (2020) find that 8.7% of older Americans were victims of fraud in the past five years.

[3]Financial professionals include 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,

granted new tools to fight elder abuse. The first is the express authority to reach out to a trusted contact to discuss red flags and confirm mental and physical health status.[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 a last resort, after a professional looks into the details of the situation.[5]

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 participants 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 elder financial exploitation from the Department of Treasury, the employment history of the entire universe of registered brokers and investment advisers from the Financial Industry Regulatory Authority (FINRA) and the Securities and Exchange Commission (SEC), county-level data on congregations and adherents from the U.S. Religion Census, media coverage for elder abuse during 2015-2020 from Factiva, social

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and Washington.

[4]It is important to note that trusted contacts are unable to view account information, execute transactions or inquire about account activity unless they have a power of attorney. 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.

connectedness measures from Facebook, data from a credit bureau about the finances of the elderly, and county-level data about the elderly from the U.S. census.

The dependent variable that we analyze is the county-level, monthly frequency of elder abuse.[7] Alternatively, one could imagine using the incidence of trusted-party contacts or halted disbursements 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 when they roll out a trusted contact system and communicate with 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.

If deputization is effective, we expect a drop in reports of elder financial exploitation for a few reasons. The new authorities may allow financial professionals to stop abuse faster and earlier, reducing the number of cases reaching the $5,000 loss threshold above which reporting is mandatory. Additionally, family members and other perpetrators may learn in conversations with advisors or when enrolling in trusted contact systems about the new protections on the account, which alters the perceived riskiness of fraud and deters them from attempting abuse. Relatedly, as the deputies take their role seriously and set up trusted contact systems and procedures for halting disbursements, their deputization can act as a deterrent.

Deputizing appears to be effective at deterring the financial exploitation of the elderly. We estimate that this policy led to a 6%-9% reduction in the monthly number of elder financial abuse cases in treated counties.[9] The result is robust to including county and month fixed

[7] A CFPB report studying a random sample of suspected cases finds that approximately 80% result in a financial loss. See https://files.consumerfinance.gov/f/documents/cfpb_suspicious-activity-reports-elder-financial-exploitation_report.pdf.

[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. With these caveats, the NASAA 2019 Enforcement Report shows that in 2018 approximately 14% of the total number of reports made under the Model Act involved a delayed disbursement of funds. Additionally, a case-study analysis that we performed in conjunction with Texas Adult Protective Services found that investigations initiated in response to validated reports from financial institutions did include information about delayed disbursements. Admittedly, though, the data maintained by the State of Texas is limited: sample sizes are small, documentation is poor, and data on the number of contacts to trusted parties are missing.

[9] In our sample, there are 0.7 cases per county-month on average. For the 3,139 counties in our sample, this translates into a reduction of 1,582 (4% $\times$ 0.8 $\times$ 3,139 $\times$ 12) to 2,373 cases per year.

effects, to dropping any state, to matching counties on pre-treatment characteristics, and to using more aggregate levels of observation, such as a county-year or state-month panel. As placebo tests, we show that randomizing the treatment dates results in no effect, there is no drop in unrelated types of suspicious activity reports (e.g., insider trading), and there is no drop in reports from money services businesses, which are not deputized.

Several pieces of evidence suggest that brokers appear to be less effective deputies than other financial professionals, namely investment advisers. First, the drop in abuse is strongly related to the per capita number of investment advisers in a county but unrelated to the per capita number of brokers. Second, there is only a drop in abuse when a state adopts the NASAA Model Act, which applies to financial professionals more generally, and not when FINRA adopts Rules 2165 and 4512, which apply to brokers only. Third, the drop in abuse is similar for states adopting the Model Act both before and after the FINRA rule change. Finally, we find no drop in reports from the broker-dealer industry. These findings are consistent with brokers having more arms-length and transactional relationships with clients than investment advisers, which may reduce brokers' ability to detect fraud and financial incentives to act.[10]

Within the set of investment advisers, there is substantial heterogeneity in the effectiveness of deputization. There is a larger drop in abuse when investment advisers serve wealthier clients. This may be because those clients provide more fee revenues and because those advisers know their clients better and thus what is suspicious. Relatedly, the drop is stronger when advisers worked longer in a specific county. By contrast, their experience, or tenure in the profession, seems less important. Additionally, the drop occurs more quickly when advisers work at larger firms.

Deputization appears to be more effective when there are fewer other safeguards in place. First, the drop is weaker for abuse involving products and instruments already subject to intense scrutiny (e.g., home equity lines of credit and bank cashier checks). Second, consistent with work finding that the risk of fraud increases for emotionally and socially isolated elderly persons (Alves and Wilson, 2008; Lichtenberg et al., 2013; James et al., 2014; Lichtenberg et al., 2016; DeLiema, 2018), the effect of deputizing financial professionals is stronger in more socially isolated communities. We use the number of Facebook connections between members of a county and the number of congregations per capita as two proxies for social connectedness.

Finally, it is important to point out that the magnitudes of the effects of deputization

[10] 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.

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, our measure of abuse is indirect in that we cannot observe the drop in attempted abuse that exceeds the $5,000 mandatory reporting threshold but is later interrupted. Third, a growing literature documents that some financial professionals engage in frequent misconduct and even prey on the elderly (Dimmock and Gerken, 2012; Dimmock, Gerken, and Graham, 2018; Charoenwong, Kwan, and Umar, 2019; 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. But, deputies in an industry with less misconduct may be even more effective.

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, involving $1.7 billion in losses.[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 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

[11] Ex. 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.

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

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

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. (The percentages add up to more than 100% because reports of elder financial exploitation may indicate multiple types of suspects.) 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 may be more disproportionately victimized.[18]

While there is no evidence of underreporting of abuse cases to the Department of Treasury's Financial Crimes Enforcement Network (FinCEN) database, which is the data source for elder abuse cases in this paper, it is possible. Consequently, the frequency and magnitude of elder abuse could be even higher. Any underreporting is unlikely to be a problem for our analysis. First, if the new rules raised awareness about elder abuse, then we would expect an increase in reporting following their passage. But, if anything this works against our finding that the new laws decreased reports of egregious activity. Additionally, for underreporting to be a problem, it would have to be correlated with the staggered adoption of the *Model*

[16] Adults that are above 65 years old are 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] The descriptive evidence across demographics may be mixed in the literature. DeLiema et al. (2012) find greater abuse of low-income Hispanic immigrants. Incidentally, DeLiema et al. (2020) do not find any higher incidence of abuse against females or Hispanics more generally for the exploitation outcomes that they consider.

Act across states. That is, underreporting would have had to increase when states adopted the *Model Act* to result in our observed drop in elder financial exploitation. This is unlikely since the preexisting reporting requirements to the U.S. Treasury did not change.

2.2. Financial Professionals

The financial professionals deputized 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 expressly deputized *all* types of financial professionals (Delaware, Kentucky, Texas, Virginia, and Washington), while other states primarily deputized brokers and investment advisers, who provide a wide variety of services. Brokers and advisers constitute 9.1% of total employment of the finance and insurance sector,[19] and SEC-registered investment advisers manage about 25% of global wealth.[20] Approximately 50% of broker representatives are dual-registered as investment advisers and about 85% of investment adviser representatives are also registered as brokers. This subsection provides background on these deputies.

In the United States, firms known as registered-investment advisers (RIAs) employ investment-adviser representatives (IARs), who engage in the business of advising about securities for compensation.[21] 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

[19]In 2016, there were 350,731 unique advisers and 701,181 unique brokers. Approximately 85% of advisers are dual-registered as brokers (298,181). The entire finance industry employed 8,203,000 individuals, so that advisers and brokers make up 9.5% of the finance industry (350,731+701,181-298,181)/8,203,000. Sources: Bureau of Labor Statistics, IAPD, and BrokerCheck.

[20]As of 2014, investment adviser firms registered with the SEC reported managing approximately $61.9 trillion in assets for their clients. (Source: https://www.govinfo.gov/content/pkg/FR-2015-09-01/pdf/2015-21318.pdf.) Global wealth in 2014 is estimated at $251 trillion (Source: https://onlinelibrary.wiley.com/doi/full/10.1111/roiw.12318.)

[21]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."

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.

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.[22] The two rules vary in certain other terms of their implementation and the types of financial professionals covered. These differences are summarized in Table 1 and detailed below.

[Insert Table 1 Here]

3.1. The Model Act

The *NASAA Model Legislation or Regulation to Protect Vulnerable Adults from Financial Exploitation* (hereinafter, "Model Act") originated as an initiative of the North American Securities Administrators Association's (NASAA) 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

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

contact and the authority to delay disbursements of funds.[23] Strict privacy laws impeded such efforts to consult with trusted persons prior to the rules.[24] Because the deputizing policies are permissive, there is never any obligation for the financial professionals to reach out to a trusted contact if the financial professional believes the contact to be the perpetrator. The ability to delay a disbursement of funds allows for an investigation to occur prior to any loss of funds due to exploitation.

We identify state-level acts, laws, statutes, and regulations that are based on the Model Act or contain similar provisions to the Model Act across U.S. states. For each state, we obtain the name of the relevant legislation or regulations, the passage date, and the effective date from the state's legislature website. As shown in Table 2, as of December 2019, 25 states have enacted legislation that contains many of the provisions found in the Model Act. (33 states have enacted legislation as of July 2021, but reports of elder financial exploitation are only available through 2019.) 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.[25] 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 2 Here]

[23] Broker-dealers and investment advisers may delay disbursement of funds from a senior's account for up to 15-25 days if they reasonably believe that such disbursement will result in the financial exploitation of the senior. 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. 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.

[24] These privacy laws explain why there is essentially no media coverage of financial professionals disrupting elder abuse. 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. 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 A14. Neither the SEC's Investment Adviser Public Disclosure (IAPD) website nor FINRA's BrokerCheck website discloses such information regarding brokers and advisers.

[25] 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.

Figure 1 shows graphically the staggered adoption of the Model Act or similar provisions across U.S. states.

[Insert Figure 1 Here]

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.[26] Upon placing a hold, FINRA Rule 2165 requires the broker-dealer to immediately initiate an internal review of the facts and circumstances.[27]

The essence of the FINRA Rules 2165 and 4512 is similar to that of the Model Act, but FINRA Rules 2165 and 4512 only apply to brokers.

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

[26] 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.

[27] 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.

(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.[28] 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 Rules 2165 and 4512.

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.[29] Figure 2 shows that reports of elder financial exploitation have been increasing ever since the category was introduced in 2012.[30]

[Insert Figure 2 Here]

Reporting suspicious activity is mandatory when a suspicious transaction involves at least $5,000 in funds or assets.[31] If such a suspicious disbursement is attempted or occurs, then it

[28] 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.

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

[30] The rapidly increasing number of EFE SAR submissions may be due to a number of factors, including the growing number of older adults, a possible increase in the incidence of elder financial exploitation, growing awareness of FinCEN's 2011 Advisory, and the addition of elder financial exploitation as a category on the SAR form. See https://files.consumerfinance.gov/f/documents/cfpb_suspicious-activity-reports-elder-financial-exploitation_report.pdf

[31] In terms of reporting requirements, there are no explicit qualifications about the level of suspi-

must be reported. The rule changes we examine provide financial professionals with new tools to deter attempted abuse. Reports would fall if abuse is interrupted earlier, before reaching the $5,000 reporting threshold. Family members learn in conversations with advisers or from mailed informationals about the new protections on the account, which deters them from attempting abuse. Strangers (like robo scammers or Nigerian scammers) may learn that deputies make it more difficult to get an elderly person to disburse funds, and therefore the deputization may have a deterrent effect.

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 include 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.

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

cion. Additionally, there is no established measure of suspicion that we could use in any empirical specification. Regulations simply state that a professional "has reason to suspect." See instructions about filing SARs by FinCEN https://www.fincen.gov/sites/default/files/shared/FinCEN%20SAR%20ElectronicFilingInstructions-%20Stand%20Alone%20doc.pdf dual-registered as brokers.

4.3. 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.

4.4. U.S. Religion Census

We use data from the 2010 U.S. Religion Census to measure the number of religious congregations and religious adherents in each county.[32] 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.

[32]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. More details regarding the census can be found here: http://www.usreligioncensus.org/datacol.php. These proxies for religiosity are standard in the literature (Hout and Greeley, 1998; Grullon et al., 2009).

4.5. Control Variables

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. These data also provide the gender makeup, ethnic composition, average retirement income, and total income for individuals 65 years of age or older.

We also use data from a major credit bureau, Experian, that tracts a random sample of 2% of adults. For individuals in a county 65 years of age or older, we determine the average credit score, fraction subprime, fraction low income, average age, fraction married, and household debt-to-income ratio.

4.6. Summary Statistics

Our sample includes monthly observations for 3,139 counties from April 2012 to December 2019, resulting in 291,927 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 0.7, with a standard deviation of 2.7. Approximately 85% of counties have zero reported cases in a month. The 99th percentile of reported senior financial fraud in a county-month is 20. The per capita number of abuse cases is on average 4 per 100,000 persons 65 years of age or older, and the 90th percentile is 8.4 cases per 100,000 elderly persons. This rate of elder financial exploitation is about a third of the rate of gun deaths,[33] and ten times more frequent than voter fraud.[34]

In terms of access to financial professionals, the average number of investment advisers (brokers) per 1,000 individuals is 0.5 (1.0). 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, 85% of advisers are dual-registered as brokers, whereas about 50% of brokers are dual registered as advisers.

In an average county, roughly 18% of the population is 65 years of age or older. This statistic varies substantially across counties, ranging from around 9% to 31%. 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 $89,300 in household income, $21,992 in retirement income, and a credit score of 728. An average county has 20% subprime borrowers (credit score below 660) and an average debt-to-income ratio of approximately 6.3%.

[33] The rate of gun deaths in the U.S. in 2017 was 12 per 100,000 people, the highest rate since the 1990s. See https://worldpopulationreview.com/state-rankings/gun-deaths-per-capita-by-state

[34] A Brennan Center for Justice report pegs the rate at 0.0003%. The equivalent measure of elder financial exploitation is 0.004% (4/100,000 $\times$ 100), or ten times more frequent. See https://www.brennancenter.org/sites/default/files/2019-08/Report_Truth-About-Voter-Fraud.pdf

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 reach out to trusted contacts and 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, in some specifications, the timing of FINRA Rules 2165 and 4512.

Table 2 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.[35] 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.[36]

We estimate models of the following form:

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

We index county by c, state by s, and month by t. $POST_{st}$ is an indicator variable that equals to one in the month the Model Act goes into effect in a state, permitting financial professionals to reach out to a trusted contact and halt suspicious disbursements.[37] Figure 1 shows variations in these treatment dates across states. The β on $POST_{st}$ measures the effect of deputization.[38] $\mathbf{X}_{ct}$ denotes a vector of time-varying county demographic and economic

[35]Some states adopting the Model Act mandate reporting to Adult Protective Services (APS) and sharing records with state regulators. These changes in reporting requirements are independent of the reporting requirements to the U.S. Treasury. 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." Importantly, any decline in reports to FinCEN cannot be explained by substitution in reporting to APS. Additionally, any substitution would be stronger for cases with lower dollar amounts where there may be more subjectivity, but our results are stronger when clients are wealthier (more AUM-per-client) and in wealthier counties, where exploitation is likely to involve larger dollar amounts.

[36]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 A6, we find similar results when only including sample months prior to February 2018.

[37]We divide our analysis into the effects of the Model Act and FINRA Rules 2165 and 4512. We examine their interactions later. This is because FINRA Rules 2165 and 4512 are directed only at brokers and apply nationally.

[38]The staggered difference-in-differences approach uses three distinct sources of variation: the difference across states treated at different times during the sample period (e.g., earlier treated states serve as controls for later treated states, and later treated states serve as controls for earlier treated states), the difference

characteristics, such as the number of persons 65 years of age or older in a county. The controls are measured for the elderly persons in a county. Our main specification includes a set of county fixed effects, denoted by η_c, to absorb any unobserved persistent county characteristics. We also include year-month fixed effects, denoted by η_t, to account for nationwide trends, such as the general increase in reports of elder financial exploitation during our sample period (Figure 2). We double-cluster standard errors at the state and month levels.

When interacting $Post_{st}$ with a variable of interest, we also interact $Post_{st}$ with each control, which reduces the possibility that the interaction of interest is driven by an omitted factor (Yzerbyt et al., 2004). For example, when interacting $Post_{st}$ with the per capita number of deputies in a county, we also interact $Post_{st}$ with the controls related to the number of elderly, their educational attainment, and income to address the concern that the per capita number of deputies is merely a proxy for these other attributes. Relatedly, we also interact each of our controls with the variable of interest (e.g., the per capita number of deputies). Without these interactions, we would be assuming that the controls matter similarly for elder financial exploitation in counties with low and high per number of deputies.

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 3 shows, in event time (both at monthly and quarterly frequencies), no unusual changes in elder financial exploitation prior to the rule change, and a noticeable drop only following the rule change. Note that Figure 3 visualizes the dynamic difference-in-differences as implemented recently in Ivanov et al. (2020). This is important to show as Goodman-Bacon (2018) cautions against only relying on a "single coefficient two-way fixed effects specification to summarize time-varying effects". However, in most tests in the paper, we implement the "canonical" difference-in-differences specification as it is easier to execute and interpret when considering cross-sectional interactions.

[Insert Figure 3 Here]

Second, for the 25 states adopting the Model Act by December 2019, we find no relationship between the timing of adoption and a wide range of state economic and demographic characteristics, such as the preexisting level of elder abuse, the fraction of seniors in the population, average household income and credit scores, the share of the population that is

across treated states and never-treated states, and the difference across states treated during our sample period and states always-treated during our sample period. See Appendix B for a decomposition of this effect by the source of variation, as outlined in Goodman-Bacon (2018).

male or married, and population. In Figure 4 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.[39] 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. In Appendix Table A3, we also follow Acharya et al. (2013) and estimate Weibull Hazard models, which confirm that the timing of adoption of the Model Act is not a function of political, economic, or other prior observable factors.

[Insert Figure 4 Here]

Lastly, we show that possible differences in the rate by which reporting of elder financial exploitation increased across states during the sample period is not correlated with the timing of adoption of the Model Act. Specifically, in Appendix Table A4, we regress the number of months until a state adopts the Model Act on the state-level growth in reporting from 2012 to 2016. There is no relation. Additionally, in untabulated results, moving from a regression of the number of abuse cases on county and month fixed effects to the number of abuse cases on county and state-by-month fixed effects only increases the adjusted R^2 from 47% to 50%, suggesting that there are not large differences in reporting trends across states despite large increases in reporting over the sample period.

5.2. Main Effects

We find that deputizing appears to be effective at deterring financial exploitation of the elderly. Table 4 panel A shows the results. The outcome variable is the natural logarithm of one plus the number of elder financial exploitation cases in a county in a month. With only time fixed effects, column (1) shows an 11.6% decrease in financial exploitation in counties in treated states. Columns (2) and (3) both show an 8.6% 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 6% to 35% when including the controls. The R^2 does not increase much from column (3) to (6),

[39]For instance, in Florida, by September 2019, the bill had passed through Florida's House of Representatives twice, but not the state senate, due to busier than usual legislative sessions. See https://www.financial-planning.com/news/how-advisors-can-prevent-elder-financial-exploitation.

consistent with most controls being slow moving so that the county fixed effects absorb most differences across counties.[40] Overall, the estimated decline in financial exploitation remains quantitatively similar across specifications and is statistically significant at the 5% level in most specifications. The economic magnitudes of a 6%-to-9% reduction suggest an annual reduction of between 1,582 ($0.06 \times 0.7 \times 12 \times 3139$) and 2,373 elder financial exploitation cases across the 3,139 counties in our sample, assuming on average 0.7 cases per county-month.

[Insert Table 4 Here]

Table 4 panel B shows that this drop in elder financial exploitation is robust to the construction of the dependent variable. Column (2) finds a similar drop using 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 2.9 percentage points, which represents about 20% of the unconditional probability of having at least one senior financial fraud case in a county-month, which is approximately 15%. Column (3) uses the raw count and finds a drop of nearly one case per month. Column (4) uses the per capita amount of abuse since county sizes vary and finds a drop of about 0.6 cases per 100,000 elderly persons. Column (5) finds a similar drop using the log of one plus the per capita amount of abuse.

Additionally, we show that the effect is robust to forming matched samples based on counties' 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. While we show parallel *pre*-treatment trends in Figure 3, the parallel trend assumption — that treated and control groups would

[40] The primary value of the precise set of controls comes from later cross-sectional tests in the paper. In those test, we interact the controls with *Post* to help with the interpretation of the result. For example, we can rule out that the effect is stronger in counties with more advisers per capita solely because those counties with more advisers are also home to wealthier elderly. Here is some specific reasoning behind the controls.

1. "Log Pop Above 65", captures the size of the elderly population.
2. "Vantage Score", captures the general financial health. A higher score may suggest a wealthier base of elderly to exploit.
3. "Fraction Married", captures the extent to which the elderly are socially isolated.
4. "Fraction of Subprime", indicates the amount of assets available to exploit.
5. "Fraction of Low Income", indicates the amount of assets available to exploit.
6. "Average Age", may be correlated with the degree of cognitive impairment in that county.
7. "Male", DeLiema et al. (2020) finds females more subject.
8. "Household income", may indicate the amount of financial resources available to exploit.
9. "Household Debt-to-Income", may indicate the amount of available funds to exploit.
10. "Bachelor or Higher", may indicate the educational attainment of the elderly and the family members.

have experienced parallel changes *post*-treatment — is inherently untestable. We use the following minimum distance matching procedure: for each county, we calculate its geometric distance to all other counties based on a vector of covariates (the control variables in Table 4).[41] 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 5 Panels A and B show that the estimates using matched county pairs are statistically significant and economically similar to those presented in Table 4. Table 5 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 5 Here]

The drop in abuse is also robust to other specifications. In Appendix Figure A1, we show the main effect in Table 4 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 A5 shows that the main effect is robust to removing the first few years of the sample with large increases in reporting of elder financial exploitation; for example, there is still a significant drop in elder abuse for the 2016-to-2019 sample period, which discards about half of the observations. Appendix Table A6 shows a similar drop when the sample is 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 A7 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.

Lastly, because our dataset at the county-month level is relatively sparse, we collapse the dataset at more aggregate levels and repeat our difference-in-differences analysis. In collapsing the data, we reduce the number of observations drastically (by more than 95%) and therefore reduce the power of our tests, but at the same time, we are able to effectively decrease the sparsity in the outcome variable of interest. First, in Appendix Table A8, we

[41] 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.

created a state-month panel. We restrict the sample to 2014 to 2019 and drop states with no reports in a year. Only 3% of state-months have zero reports (as opposed to 85% of county-months). Despite removing a substantial amount of variation, there continues to be a significant drop in the state-month number of reports across a number of formulations of the outcome variable. Second, in Appendix Table A9, we create a county-year panel. We again drop counties with zero reports in the full sample. We restrict the sample to 2014 to 2019 to remove the early years with more zeros. Now, only 30% of county-year observations are zeros. Again, despite removing a substantial amount of variation, the table shows a drop in county-year reports across a number of formulations of the outcome variable.

An important caveat is that our regression estimates of the policy's effect are likely underestimates. Figure 3 shows that the effect of the policy is not complete in the month of adoption. For staggered difference-in-differences designs, 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).[42] The delay in the effect may occur for 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.[43] 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. Additionally, because passage of the Model Act likely increased awareness among financial professionals of elder financial exploitation, our estimates likely underestimate the potential effect of deputization.

5.3. The Main Effect by Type of Financial Professional

Next, we consider how effective the law is based on the types of financial professionals involved, their characteristics, and their presence in the community. As it turns out, not all deputies appear to be equally effective.

[42] This plot also helps rule out the possibility that the policy created an empty threat and deputies did not act. First, the perpetrators in our setting are typically family members or caregivers, who probably have little sense of the regulations in place to protect people. Second, let us suppose that financial professionals do not take their roles seriously and perpetrators are scared off when new laws are passed. Then, this would lead to a temporary drop in elder abuse, since rational perpetrators would soon learn that financial professionals are not performing as deputies. Instead, we find that the treatment effect is increasing over time.

[43] 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.

Table 6, panel A, column (1) shows that the drop in elder abuse is greater in counties with more investment adviser representatives per capita. However, columns (2) and (3) show no significant relation with the number of brokers per capita. Both the number of advisers and number of brokers are standardized in Table 6, panel A, to allow for such a comparison. We caveat that the coefficient magnitudes in column (3) should be interpreted with caution as the correlation between the number of advisers and brokers in a county is 0.78.

[Insert Table 6 Here]

Relatedly, Table 6 panel B column (1) shows a large drop in reports from depository institutions, which include bank holding companies and their investment advisery divisions. However, column (3) shows no significant drop in the number of reports of elder financial exploitation securities firms, which are broker-dealers. As a placebo test, there is also no drop in reports from money services businesses, which employ neither brokers nor advisers.

Interestingly, Table 6 panel C shows that the drop in elder abuse only occurs when states adopt the Model Act, not after FINRA Rules 2165 and 4512. This is likely due to the fact that the FINRA legislation is specific to brokers. In fact, column (1) shows the drop in elder abuse is not significantly different for states adopting the Model Act before or after FINRA Rules 2165 and 4512.

Together, these findings suggest that investment advisers are more effective deputies than brokers. This dichotomy is consistent with brokers having a more arms-length and transactional relationship with clients than investment advisers.[44] Brokers are more likely to assist with one-off transactions, compensated accordingly with commissions, fixed fees, or hourly compensation. Also, brokers serve more clients; Form ADV data shows that investment advisery firms employing above the median number of advisers dual registered as brokers service 60% more clients per employee on average in 2015. By contrast, advisers have a fiduciary duty to their clients that requires them to both understand their clients' situations and objectives and to put their client's interests first.[45] Advisers are more likely to provide regular financial planning advice and, thus, are more likely to develop deeper and more intimate relationships with clients, which improves their ability to detect suspicious activity. An alternative interpretation for the dichotomy is that in communities with more investment advisers, there was more elder financial exploitation and therefore deputization had a larger impact. However, this does not seem to be the case (See Appendix Table A10).

In addition to variation in the effect of deputization across types of financial professionals, we also observe differences within the set of investment advisers. Table 7 column (1) shows a

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

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

larger drop in abuse when investment advisers serve wealthier clients.[46] This may be because those clients provide more fee revenues and because those advisers know their clients better and thus what is suspicious. Alternatively, family members and caregivers perpetrating abuse against wealthier persons are more financially sophisticated. Relatedly, Table 8 panel A column (1) shows that the drop is stronger when advisers worked longer in a specific county.[47] Our individual-level panel dataset of advisers allows us to measure how many months each adviser has worked in a certain county. By contrast, columns (2) and (3) show that their experience, or tenure in the profession, seems less important. (An important caveat is that *Time in County* and *Time in Profession* have a correlation of 0.89.)

Appendix Table A11 shows that these results are robust to controlling for an advisery firm's assets under management. Appendix Figure A3 shows that the drop occurs more quickly when advisers work at larger firms. Larger firms may learn and implement the new rules more quickly. However, Appendix Table A12 shows that these multi-state firms do not implement the new protocols in a state prior to adoption of the Model Act. (Consistent with brokers being less important for the effect, Table 7 columns (2) to (4) do not find that the drop is larger when advisers have more broker-like compensation arrangements. Additionally, Table 8 panel B shows no variation in the effect and brokers' time in the county.)

5.4. The Effect of Deputization and Existing Safeguards

This section examines whether the effects of deputization vary based on existing safeguards on financial instruments and existing protections within communities. Certain types of financial transactions are more safeguarded than others. We would expect less abuse in these areas and also less of an effect of deputization. Table 9 panel A shows no evidence of a drop in abuse involving home equity lines of credit (HELOCs) and insurance claims. Panel B shows less of an effect on abuse involving bank cashier checks and money orders. These products and instruments already have natural protections in place. For example, getting a HELOC involves a long and arduous process, including a closing process with loan documents that evaluate other liens on the property. Filing an insurance claim requires documentation and perhaps visits from an agent. Getting a bank cashier check or money order requires speaking with a bank representative and providing documentation. In these

[46] 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.

[47] Advisers may be more willing to help those with whom they have a relationship, or community connections more generally, because professionals in such communities are more likely to derive utility from the increases in the welfare of others (Leider et al., 2009).

cases, it is going to be much more difficult to get away with fraud even without the Model Act. Consistent with this reasoning, Table 3 panel B shows that these categories are less frequently associated with abuse. So we would not expect deputization to have bite here. By contrast, we find significant drops in abuse involving debit cards, deposit accounts, fund transfers, and personal checks, which involve relatively simpler approaches to extracting an elder person's financial resources.

[Insert Table 9 Here]

In addition, certain types of elderly persons may be more subject to abuse than others. Prior work finds that the risk of fraud increases for emotionally and socially isolated elderly persons (Alves and Wilson, 2008; Lichtenberg et al., 2013; James et al., 2014; Lichtenberg et al., 2016; DeLiema, 2018). For this reason, a client's relationships with others in the community may matter for the effectiveness of the policy. 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. In other words, social connections may serve as a substitute of the new regulation. Table 10 column (1) shows that the effect of deputization is significantly weaker in more connected counties, measured using the Social Connectedness Index from Facebook that captures the probability that two members of a county are friends on Facebook. Column (2) also shows that the effect of deputization is weaker in counties with more religious congregations per capita, which may capture 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.[48] 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 religious adherents is only 0.2.) Evidently, 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.

[Insert Table 10 Here]

Another type of safeguard may be a more ethical community. The religious congregation

[48] 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).

result could be consistent with that form of protection.[49] Consistent with this reasoning, the coefficient estimate on the number of religious adherents 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 moral imperatives providing safeguards that substitute for the deputization of financial professionals.

Overall, deputization is less effective when the financial instruments are already heavily scrutinized and when the elderly are less socially isolated.

5.5. Alternative Explanations

While the policies are permissive, financial professionals may perceive them as mandatory because regulators might increase oversight of the industry if financial professionals do not act. In other words, the adoption of the new laws may signal increased regulatory concern with elder financial exploitation and thus the potential for 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 other egregious activity. We examine this possibility in Table 11 by gathering all of the disclosures individual advisers and brokers must make regarding regulatory actions and misconduct. 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.[50]

[Insert Table 11 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, deputies may again not perceive the new regulations as

[49] 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).

[50] Due to data limitations, we conduct Table 11 tests on the subsample of advisers that are dual-registered as brokers, which comprise 85% 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.

permissive but rather mandatory. 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 6 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. 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. Overall, our findings give hope for the use of deputization in the future in other venues.

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Figure 1. Staggered Adoption

The map shows the staggered adoption of the Model Act across states by December 2019.

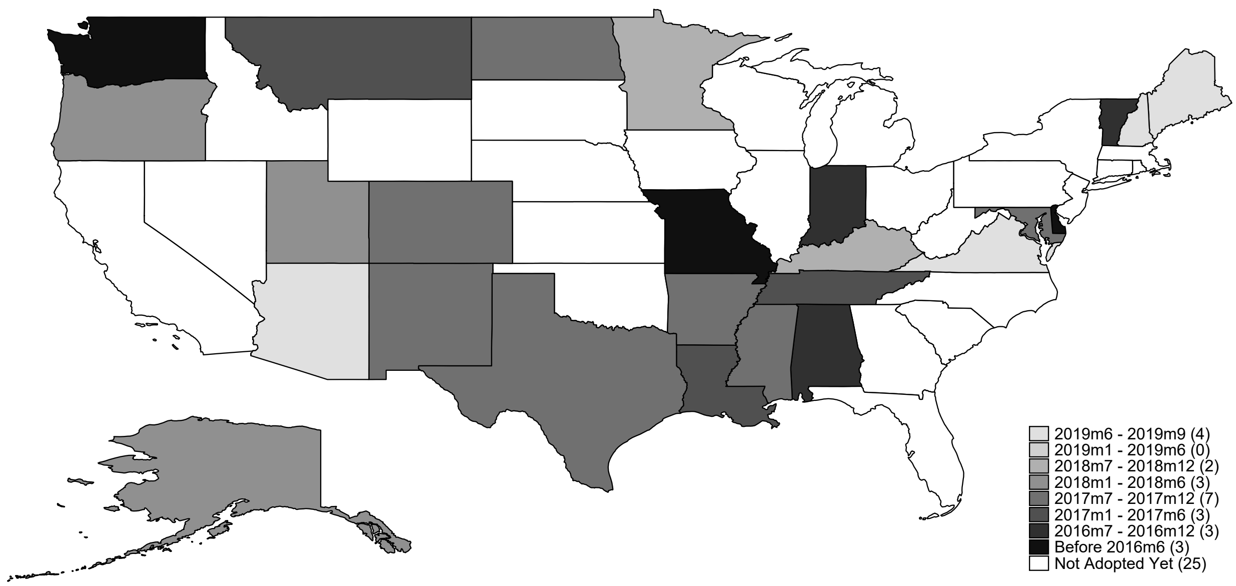


Figure 2. Log Number of Elder Financial Exploitation Reports to FinCEN by Month
This figure depicts the natural logarithm of the total number of suspicious activity reports submitted to FinCEN that are flagged as related to elder financial exploitation. The counts are based on our final sample of counties, which exclude, for instance, U.S. territories.

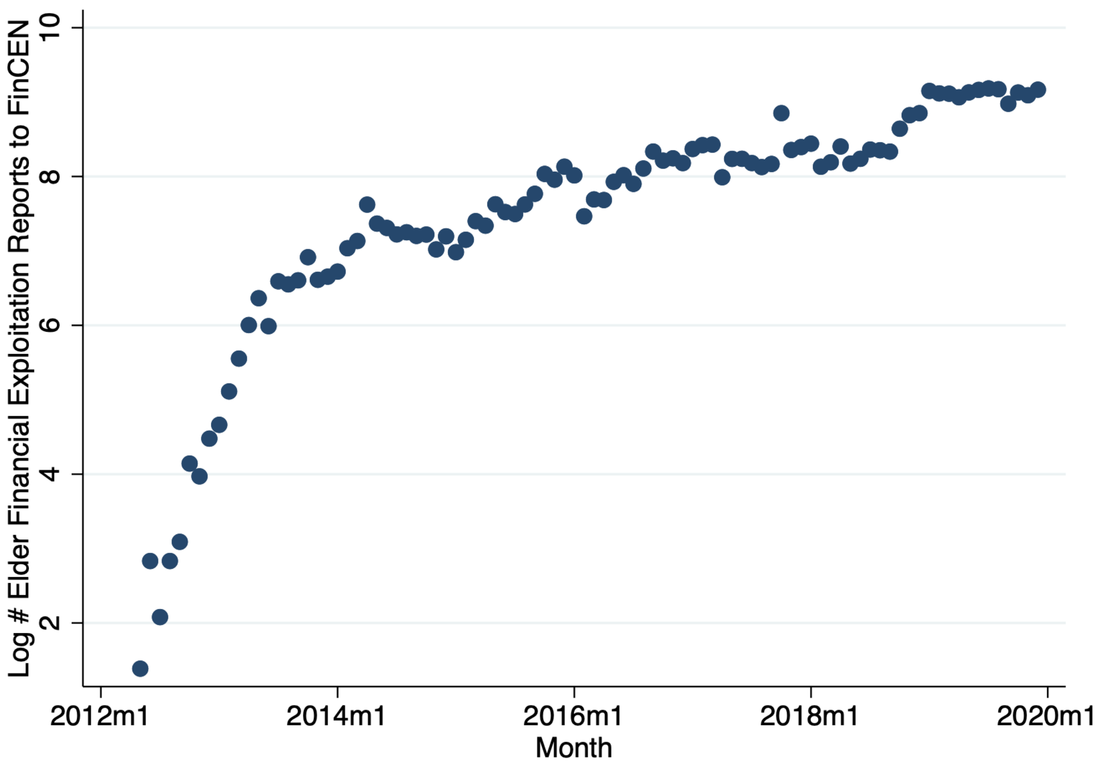


Figure 3. Dynamic Difference-in-Differences Estimates

This figure estimates the effect of deputizing financial professionals on elder financial exploitation around the date a state adopts the Model Act. In Figure 3a, the red vertical line at quarter zero 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. The coefficients plotted are those on indicator variables indicating the event time. If a state does not adopt the Model Act by 2019, then the event time indicators are all zero. The included controls are described in Table 3's legend. Year-quarter fixed effects are included. 90% confidence intervals based on standard errors double clustered at the state and quarter levels. We omit the quarter two periods before the quarter of treatment. Figure 3b is similar but at the monthly frequency.

Figure 3a: Quarterly dynamic difference-in-differences plot

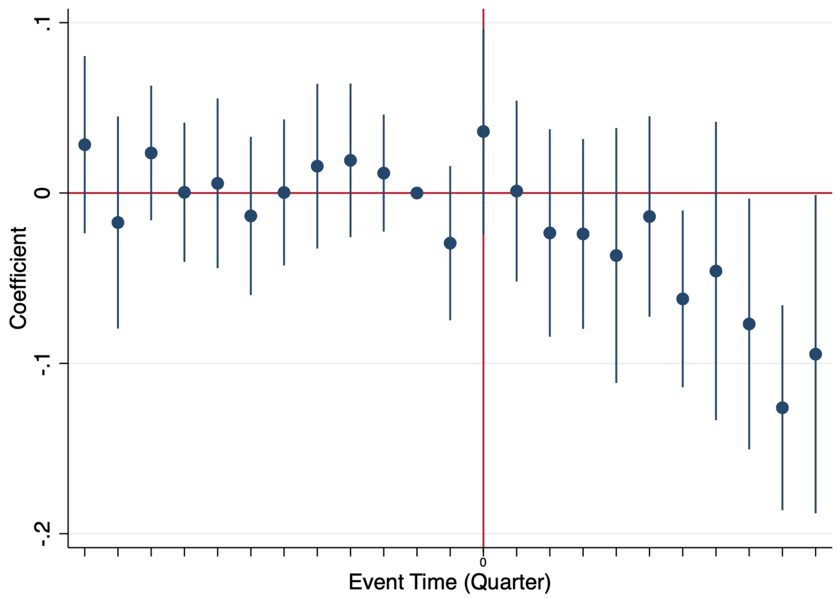


Figure 3b: Monthly dynamic difference-in-differences plot

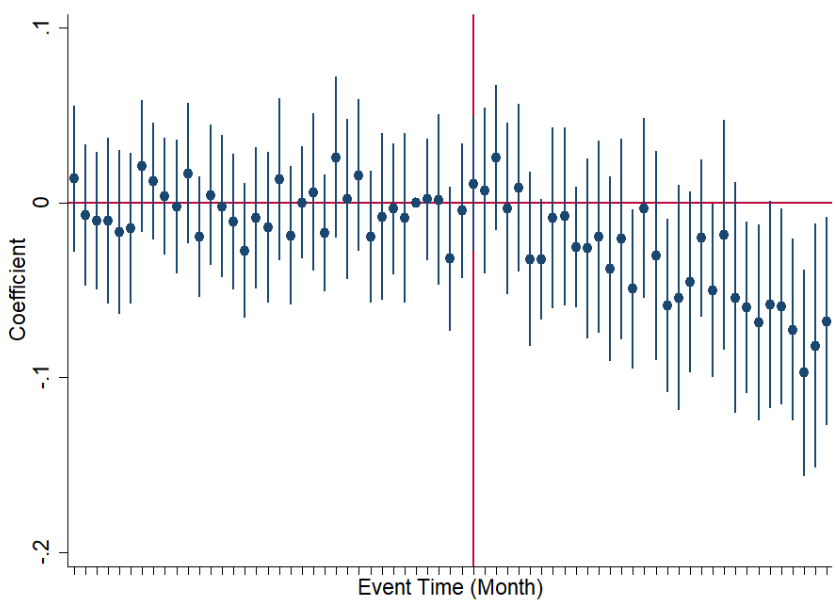
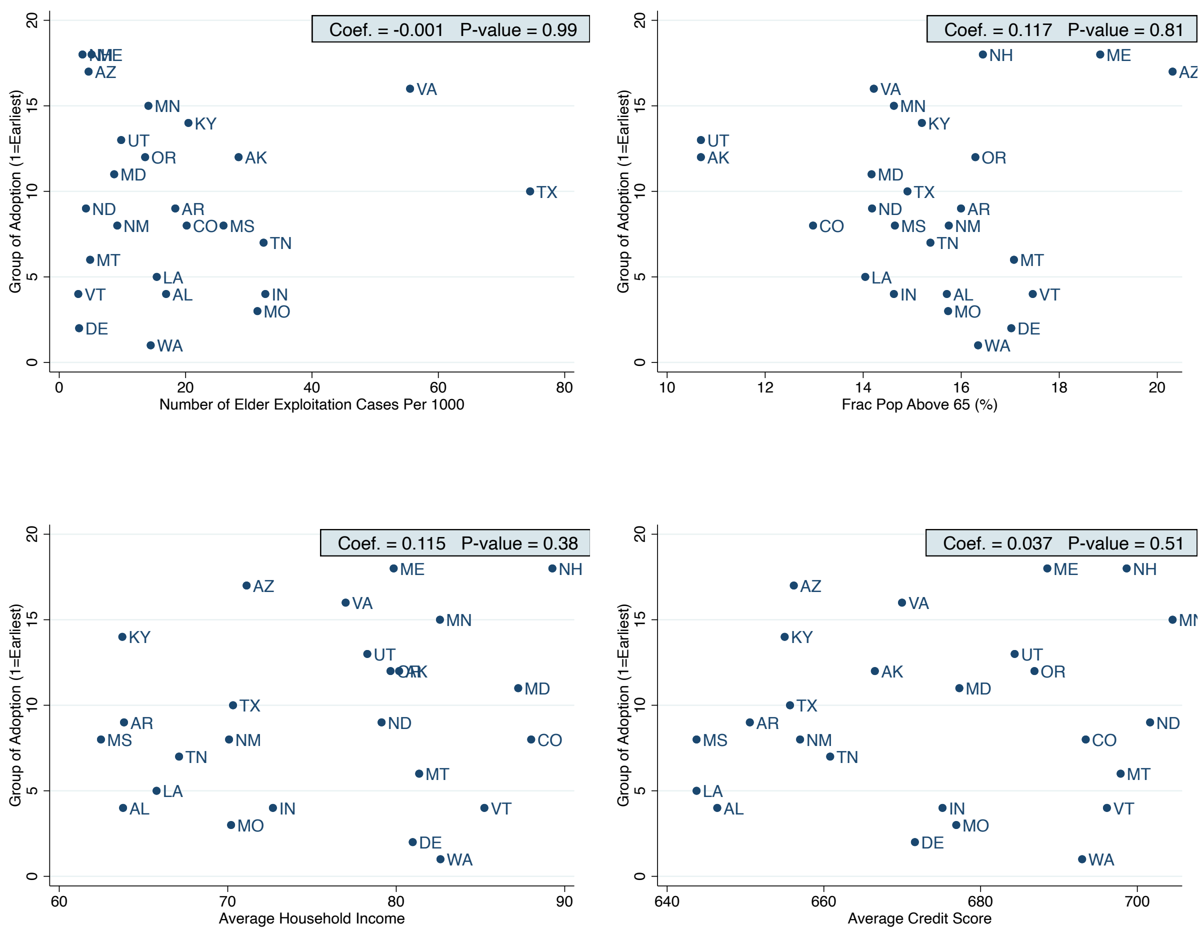


Figure 4. Do state characteristics predict the timing of adoption?

Scatter plots of the timing of states' adoption of the Model Act against states' characteristics, for the 25 states that adopted the Model Act by December 2019. The corresponding regression results are reported in 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.



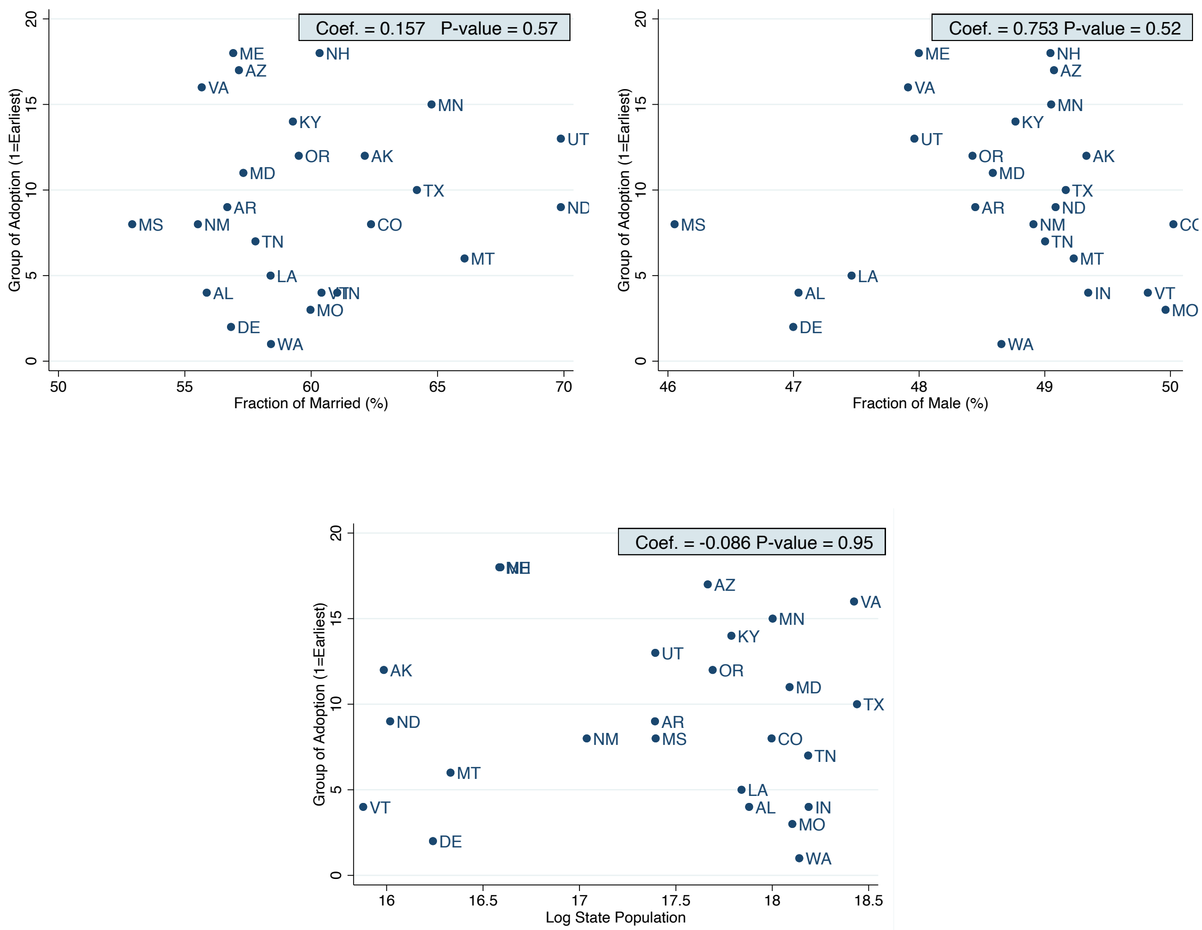

Coef. = 0.157   P-value = 0.57
Group of Adoption (1=Earliest)
Fraction of Married (%)
Coef. = 0.753 P-value = 0.52
Group of Adoption (1=Earliest)
Fraction of Male (%)
Coef. = -0.086 P-value = 0.95
Group of Adoption (1=Earliest)
Log State Population

TABLE 1. 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 2. Staggered Adoption of NASAA Model Act

This table shows the staggered adoption of the 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 3. 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. *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 Cases Per 100,000 Adults 65+* is the per capita number of abuse cases per 100,000 elderly adults 65 years of age or older. *Elder Financial Exploitation Probability* is an indicator variable that equals to one if there is at least one report of elder financial exploitation in a county-month. *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 brokers 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 (65+)* is the average credit score of adults 65 years of age or older in a county-month, based on a 2% representative sample of credit bureau records. *Fraction of Subprime (65+)* is the fraction of elderly residents with a credit score below 660. *Fraction of Low Income (65+)* is the fraction of elderly residents with incomes below the national median. *Average Age (65+)* is the average age of elderly residents in a county. *Fraction of Male (65+)* is the fraction of elderly residents that are male. *Fraction Married (65+)* is the fraction of elderly residents that are married. *Household Income (65+)* is the average household income for elderly residents of a county. *Household Debt-to-Income Ratio (65+)* is the average household debt-to-income ratio for elderly residents of a county. *Average Retirement Income (65+)* is the average personal retirement income for retirees in a county. *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 elder financial exploitation reports submitted to the U.S. Treasury's FinCEN database.

Panel A: County-Month Summary Statistics

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Mean	SD	p10	p50	p90	N
Elder Financial Exploitation Cases	0.7	2.7	0.0	0.0	2.0	291,927
Elder Financial Exploitation Cases Per 100,000 Adults 65+	4.0	21.4	0.0	0.0	8.4	291,927
Elder Financial Exploitation Probability	0.2	0.4	0.0	0.0	1.0	291,927
Adviser Per 1,000	0.5	1.0	0.0	0.3	1.2	291,927
Brokers Per 1,000	1.0	2.1	0.0	0.6	2.0	291,927
Fraction Dual-Registered Advisers	0.9	0.5	0.7	0.9	1.0	231,180
Fraction Dual-Registered Brokers	0.5	0.3	0.0	0.5	0.8	256,070
Population Above 65	15,443.5	44,218.8	988.0	4,590.0	31,990.0	291,927
Fraction of Population Above 65	0.2	0.0	0.1	0.2	0.2	291,927
Vantage Score (65+)	727.8	24.4	696.5	730.2	755.7	291,927
Fraction Subprime (65+)	0.2	0.1	0.1	0.2	0.3	291,927
Fraction Low Income (65+)	0.5	0.1	0.4	0.5	0.7	291,927
Average Age (65+)	77.1	1.9	74.8	77.1	79.2	291,927
Fraction Male (65+)	0.5	0.1	0.4	0.5	0.6	291,927
Fraction Married (65+)	0.5	0.1	0.4	0.5	0.7	291,927
Household Income (65+)	89.3	14.7	72.3	87.6	108.4	291,927
% Household Debt-to-Income Ratio (65+)	6.3	2.3	3.5	6.3	9.0	291,927
Average Retirement Income	21,992.3	5,321.3	16,294.0	21,056.0	28,987.0	291,927
Bachelor or Higher (65+)	13.6	5.4	7.6	12.7	21.0	291,927
Religious Adherent Per 1000	514.1	181.7	295.4	497.2	753.5	291,927
Religious Congregation Per 1000	2.4	1.4	0.9	2.2	4.2	291,927

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 4. Effects of Deputization on Elder Financial Exploitation

This table presents difference-in-differences estimates of the effect of the deputizing financial professionals on elder financial exploitation. 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 formulation of the outcome variable varies. The outcome in Column (2) is an indicator variable that equals to one if a county-month has above zero elder financial exploitation cases. Column (3) is the number of cases. The outcome in Column (4) is the number of cases per 100,000 persons 65 years of age or older, and column (5) is the log of the number of cases per 100,000 persons 65 years of age or older. *Post* is an indicator variable that equals to one after financial professionals are empowered to reach out to trusted contacts and halt suspicious transactions because a state adopts the Model Act. A detailed description of the control variables can be found in Table 3'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	-0.116*	-0.086**	-0.086**	-0.063**	-0.085**	-0.084**
	(0.066)	(0.036)	(0.036)	(0.031)	(0.035)	(0.032)
Log Pop Above 65				0.292***	0.312***	2.567***
				(0.028)	(0.030)	(0.376)
Vantage Score (65+)				-0.093***	-0.067***	-0.030***
				(0.016)	(0.011)	(0.010)
Fraction Subprime (65+)				-0.024***	-0.016**	-0.017***
				(0.007)	(0.006)	(0.005)
Fraction Low Income (65+)				0.012	0.018**	0.009
				(0.009)	(0.007)	(0.006)
Average Age (65+)				-0.011	-0.017**	-0.021***
				(0.008)	(0.007)	(0.007)
Fraction Male (65+)				-0.006*	-0.008**	-0.008**
				(0.004)	(0.003)	(0.003)
Fraction Married (65+)				-0.008	-0.018***	-0.002
				(0.006)	(0.005)	(0.004)
Household Income (65+)				0.051***	0.031***	0.041***
				(0.015)	(0.011)	(0.012)
Household Debt-to-Income Ratio (65+)				-0.017***	-0.021***	-0.000
				(0.006)	(0.006)	(0.004)
Bachelor or Higher (65+)				0.103***	0.097***	0.081***
				(0.013)	(0.014)	(0.023)
Constant	0.258***	0.253***	0.253***	0.245***	0.252***	0.251***
	(0.033)	(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	0.06	0.15	0.51	0.35	0.37	0.52
# Counties	3139	3139	3139	3139	3139	3139
Observations	291927	291927	291927	291927	291927	291927

Panel B:	X = Elder Financial Exploitation Cases				
	Ln(1+X)	I(X>0)	X	X/Pop. 65+	Ln(1+X/Pop. 65+)
	(1)	(2)	(3)	(4)	(5)
Post	-0.084**	-0.029**	-0.894**	-0.644*	-0.094**
	(0.032)	(0.011)	(0.396)	(0.355)	(0.038)
Controls	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.52	0.38	0.44	0.15	0.27
# Counties	3139	3139	3139	3139	3139
Observations	291927	291927	291927	291927	291927

TABLE 5. Effects of Deputization on a Matched Sample of Counties

In this table, we perform the difference-in-difference analysis in Table 4 on a subsample of matched counties by including fixed effects for each matched-pair. We use the following minimum distance matching procedure: for each county, we calculate its geometric distance to all other counties based on a vector of covariates — the controls in Table 4. 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 50^{th}, 75^{th}, and 90^{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. *Post* is an indicator variable that equals to one when a state adopts the Model Act. Standard errors, double-clustered by state and month, are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. 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.

Panel A:	Ln(1+Elder Financial Exploitation Cases)		
	(1)	(2)	(3)
	50^{th} Percentile	75^{th} Percentile	90^{th} Percentile
Post	-0.070*	-0.061**	-0.052**
	(0.038)	(0.027)	(0.026)
Pair FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Adjusted R^2	0.47	0.44	0.44
# Counties	923	1367	1629
Observations	121272	182094	218364

Panel B:	I(Elder Financial Exploitation Cases)>0		
	(1)	(2)	(3)
	50^{th} Percentile	75^{th} Percentile	90^{th} Percentile
Post	-0.026**	-0.022**	-0.019*
	(0.012)	(0.010)	(0.010)
Pair FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Adjusted R^2	0.34	0.32	0.32
# Counties	923	1367	1629
Observations	121272	182094	218364

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

	Treat = 0		Treat = 1			
	Mean	SD	Mean	SD	P-value	Std. Diff.
Log Population Above 65	0.58	(0.71)	0.57	(0.70)	(0.92)	-0.00
Vantage Score (65+)	-0.02	(0.60)	-0.03	(0.62)	(0.73)	-0.01
Fraction of Subprime (65+)	-0.05	(0.59)	-0.06	(0.59)	(0.83)	-0.01
Fraction of Low Income (65+)	-0.06	(0.63)	-0.07	(0.63)	(0.82)	-0.01
Average Age (65+)	-0.02	(0.55)	-0.03	(0.57)	(0.83)	-0.01
Fraction of Male (65+)	-0.01	(0.42)	-0.01	(0.44)	(0.96)	-0.00
Fraction of Married (65+)	0.05	(0.46)	0.06	(0.48)	(0.84)	0.01
Household Income (65+)	0.02	(0.71)	0.04	(0.71)	(0.65)	0.02
Household Debt-to-Income Ratio (65+)	0.13	(0.54)	0.16	(0.57)	(0.33)	0.04
Fraction with Bachelor or Higher	0.05	(0.97)	0.04	(0.99)	(0.84)	-0.01
Observations	652		652			

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

	Treat = 0		Treat = 1			
	Mean	SD	Mean	SD	P-value	Std. Diff.
Log Population Above 65	0.35	(0.73)	0.35	(0.72)	(0.96)	-0.00
Vantage Score (65+)	-0.11	(0.71)	-0.12	(0.73)	(0.62)	-0.02
Fraction of Subprime (65+)	0.03	(0.70)	0.03	(0.71)	(0.90)	0.00
Fraction of Low Income (65+)	0.03	(0.72)	0.01	(0.73)	(0.52)	-0.02
Average Age (65+)	-0.04	(0.65)	-0.06	(0.68)	(0.72)	-0.01
Fraction of Male (65+)	0.01	(0.56)	0.01	(0.59)	(0.97)	-0.00
Fraction of Married (65+)	0.06	(0.55)	0.07	(0.58)	(0.46)	0.02
Household Income (65+)	-0.06	(0.77)	-0.04	(0.77)	(0.71)	0.01
Household Debt-to-Income Ratio (65+)	0.11	(0.64)	0.12	(0.68)	(0.71)	0.01
Fraction with Bachelor or Higher	-0.09	(0.97)	-0.09	(0.98)	(1.00)	-0.00
Observations	979		979			

Panel E: Covariate Balance: 90^{th} Percentile Threshold

	Treat = 0		Treat = 1			
	Mean	SD	Mean	SD	P-value	Std. Diff.
Log Population Above 65	0.23	(0.75)	0.23	(0.75)	(0.89)	-0.00
Vantage Score (65+)	-0.13	(0.80)	-0.15	(0.82)	(0.55)	-0.02
Fraction of Subprime (65+)	0.05	(0.79)	0.05	(0.81)	(0.98)	0.00
Fraction of Low Income (65+)	0.07	(0.79)	0.04	(0.80)	(0.35)	-0.03
Average Age (65+)	-0.05	(0.69)	-0.07	(0.75)	(0.55)	-0.02
Fraction of Male (65+)	0.02	(0.64)	0.01	(0.69)	(0.81)	-0.01
Fraction of Married (65+)	0.07	(0.62)	0.08	(0.64)	(0.72)	0.01
Household Income (65+)	-0.05	(0.83)	-0.05	(0.84)	(0.94)	0.00
Household Debt-to-Income Ratio (65+)	0.11	(0.71)	0.11	(0.75)	(0.92)	0.00
Fraction with Bachelor or Higher	-0.11	(0.98)	-0.10	(1.00)	(0.99)	0.00
Observations	1,174		1,174			

TABLE 6. Effects of Deputization by Type of Financial Professional

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 empowered to reach out to trusted contacts and halt suspicious transactions because a state adopts the Model Act. In Panel A, *Per Capita Investment Advisers (Brokers)* is a county's per capita number of investment advisers (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. Securities firms are broker-dealers. In Panel C, *Model Act Adopted Before FINRA* (*Model Act Adopted After FINRA*) is an indicator variable that equals to one if a state adopts the Model Act before (after) the FINRA rule change in February 2018. *Post (Passage of Model Act or FINRA)* is an indicator variable that equals to one after financial professionals are first empowered to halt suspicious disbursements, either because a state adopts the Model Act or FINRA passes Rules 2165 and 4512. *Post (Passage of Model Act)* is an indicator variable that equals to one after financial professionals are empowered by the Model Act. All regressions include the time-varying county control variables in Table 4. All regressions 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)
Post	-0.047**	-0.035*	-0.041**
	(0.019)	(0.019)	(0.020)
Post × Per Capita Investment Advisers	-0.108***		-0.183***
	(0.024)		(0.048)
Post × Per Capita Brokers		-0.041	0.117*
		(0.037)	(0.063)
Interacted Controls	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Adjusted R^2	0.60	0.60	0.60
# Counties	3139	3139	3139
Observations	291927	291927	291927

Panel B: Effect by Reporting Institution

	Ln(1+Elder Financial Exploitation Cases)		
	Depository Institution	Money Services Business	Securities
	(1)	(2)	(3)
Post	-0.065**	0.003	-0.003
	(0.024)	(0.006)	(0.002)
Controls	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Adjusted R^2	0.45	0.27	0.27
# Counties	3139	3139	3139
Observations	291927	291927	291927

Panel C: Effect of NASAA's Model Act vs. FINRA's Rules 2165 and 4512

	Ln(1+Elder Financial Exploitation Cases)	
	(1)	(2)
Model Act Adopted Before FINRA	-0.080**	
	(0.033)	
Model Act Adopted After FINRA	-0.104**	
	(0.049)	
Post (Passage of Model Act or FINRA)		0.034
		(0.027)
Post (Passage of Model Act)		-0.096**
		(0.038)
Controls	Yes	Yes
Year-Month FE	Yes	Yes
County FE	Yes	Yes
Adjusted R^2	0.52	0.52
# Counties	3139	3139
Observations	291927	291927

TABLE 7. Effects of Deputization by Client Wealth and Compensation Arrangements

This table studies whether the effect of deputization on elder financial exploitation varies with client wealth and 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. *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 empowered to reach out to trusted contacts and halt suspicious transactions because a state adopts the Model Act. *Per Capita Investment Advisers* is a county's per capita number of investment advisers. *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 county and year-month fixed effects. All regressions include the controls in Table 4. 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	-0.055***	-0.048**	-0.046**	-0.046**	-0.054***
	(0.016)	(0.019)	(0.019)	(0.019)	(0.015)
Post × Per Capita Investment Advisers	-0.061***	-0.112***	-0.107***	-0.109***	-0.063***
	(0.017)	(0.025)	(0.024)	(0.024)	(0.018)
Post × AUM-Per-Client	-0.094***				-0.094***
	(0.023)				(0.023)
Post × Compensation Hourly		0.018**			0.016
		(0.008)			(0.012)
Post × Compensation Commissions			-0.005		-0.010
			(0.010)		(0.011)
Post × Compensation Fixed Fees				0.006	0.002
				(0.009)	(0.013)
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	0.61	0.60	0.60	0.60	0.61
# Counties	3139	3139	3139	3139	3139
Observations	291927	291927	291927	291927	291927

TABLE 8. Tenure in the County and in the Profession

This table studies whether the effect of deputization varies with advisers' (Panel A) and brokers' (Panel B) tenure in the county and tenure in the profession. *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 empowered to reach out to trusted contacts and halt suspicious transactions because a state adopts the Model Act. *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 county and year-month fixed effects. All regressions include the controls in Table 4. 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	-0.042	-0.042	-0.042
	(0.027)	(0.027)	(0.027)
Post × Per Capita Investment Advisers	-0.135***	-0.136***	-0.135***
	(0.038)	(0.038)	(0.038)
Post × Time in County	-0.040**		-0.030
	(0.017)		(0.022)
Post × Time in Profession		-0.039**	-0.012
		(0.016)	(0.017)
Interacted Controls	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Adjusted R^2	0.55	0.55	0.55
# Counties	3139	3139	3139
Observations	291927	291927	291927

Panel B: Brokers			
	Ln(1+Elder Financial Exploitation Cases)		
	(1)	(2)	(3)
Post	-0.038**	-0.034*	-0.040**
	(0.018)	(0.018)	(0.017)
Post × Per Capita Brokers	-0.045	-0.041	-0.043
	(0.034)	(0.037)	(0.034)
Post × Time in County	0.012		0.006
	(0.011)		(0.015)
Post × Time in Profession		0.014	0.005
		(0.011)	(0.013)
Interacted Controls	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Adjusted R^2	0.60	0.60	0.60
# Counties	3139	3139	3139
Observations	291927	291927	291927

TABLE 9. Effect by Product and Instrument

This table presents difference-in-differences estimates of the effect of deputizing financial professionals on the number of elder financial exploitation cases in a county-month, calculated separately for the different types of financial products and instruments involved. *Post* is an indicator variable that equals to one after the Model Act becomes effective in a state. All regressions include county and year-month fixed effects. All regressions include the controls in Table 4. 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 of Type X)						
X=	Debit Card	Credit Card	Deposit Account	HELOC	Insurance	Mutual Fund	Prepaid Access
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post	-0.041**	-0.018**	-0.057**	-0.000	-0.000	-0.001*	-0.001
	(0.018)	(0.008)	(0.025)	(0.000)	(0.001)	(0.001)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.38	0.25	0.27	0.02	0.11	0.09	0.12
# Counties	3139	3139	3139	3139	3139	3139	3139
Observations	291927	291927	291927	291927	291927	291927	291927

Panel B: By Instrument

	Ln(1+Elder Financial Exploitation Cases of Type X)					
X=	Fund Transfer	Bank Cashier Check	Personal Check	U.S. Currency	Money Orders	Foreign Currency
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.043**	-0.024**	-0.037**	-0.040**	-0.012	-0.003
	(0.018)	(0.011)	(0.015)	(0.016)	(0.008)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.42	0.25	0.38	0.45	0.14	0.10
# Counties	3139	3139	3139	3139	3139	3139
Observations	291927	291927	291927	291927	291927	291927

TABLE 10. Social Connectedness

This table studies whether deputization is less effective in counties with more social connectedness and religiosity. *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 empowered to reach out to trusted contacts and halt suspicious transactions because a state adopts the Model Act. *Per Capita Investment Advisers* is a county's per capita number of investment advisers. *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 county and year-month fixed effects. All regressions include the controls in Table 4. 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	-0.076***	-0.104***	-0.091***	-0.107***
	(0.026)	(0.022)	(0.025)	(0.023)
Post × Per Capita Investment Advisers	-0.200***	-0.175***	-0.249***	-0.173***
	(0.041)	(0.038)	(0.045)	(0.038)
Post × Social Connectedness Index	0.159***			
	(0.040)			
Post × Congregations Per 1000		0.123***		0.132***
		(0.029)		(0.035)
Post × Adherents Per 1000			0.056***	-0.009
			(0.017)	(0.020)
Interacted Controls	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.57	0.57	0.56	0.57
# Counties	3139	3139	3139	3139
Observations	291927	291927	291927	291927

TABLE 11. Was there a coinciding increase in 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. *I(Regulatory Actions>0)* is an indicator variable that equals to one if there are any regulatory actions taken against advisers and brokers in a county-month. 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. *I(Customer Complaints>0)* is an indicator variable that equals to one if there are any customer complaints filed against advisers and brokers in a county-month. *I(Criminal Activities>0)* is an indicator variable that equals to one if there are any 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 empowered to reach out to trusted contacts and halt suspicious transactions because a state adopts the Model Act. All regressions include county and year-month fixed effects. All regressions include the controls in Table 4. 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)
	I(Regulatory Actions>0)	I(Customer Complaints>0)	I(Criminal Activities>0)
Post	0.00088	0.00192	-0.00002
	(0.00057)	(0.00143)	(0.00021)
Controls	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Adjusted R^2	0.05	0.26	0.01
# Counties	3139	3139	3139
Observations	291927	291927	291927

Appendix A. Robustness

Figure A1. Main Effect Dropping Each State

This figure shows the distribution of the estimated policy effect in Table 4 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.

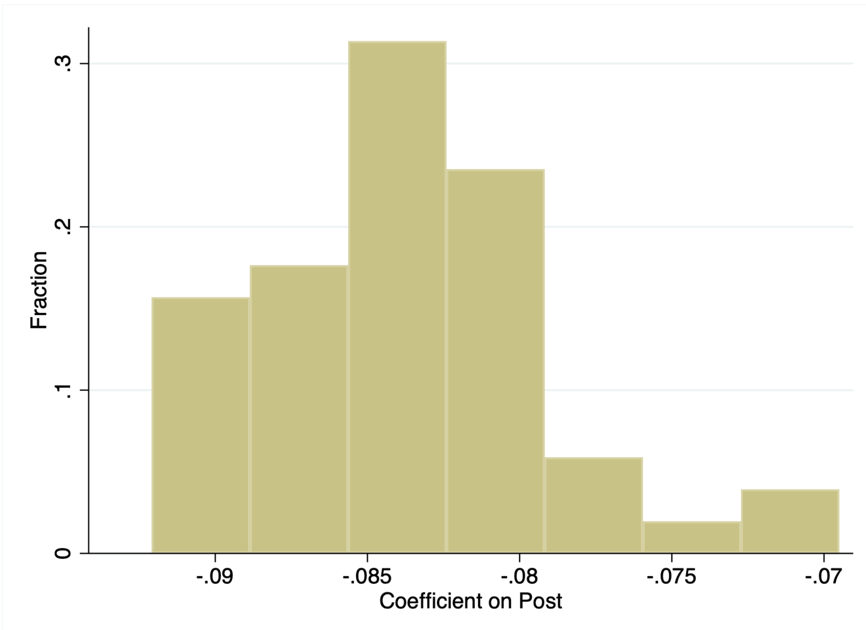


Figure A2. Main Effect Randomizing Post for Each State 100 Times

This figure shows the distribution of the estimated effect and its t-statistic as in Table 4 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.

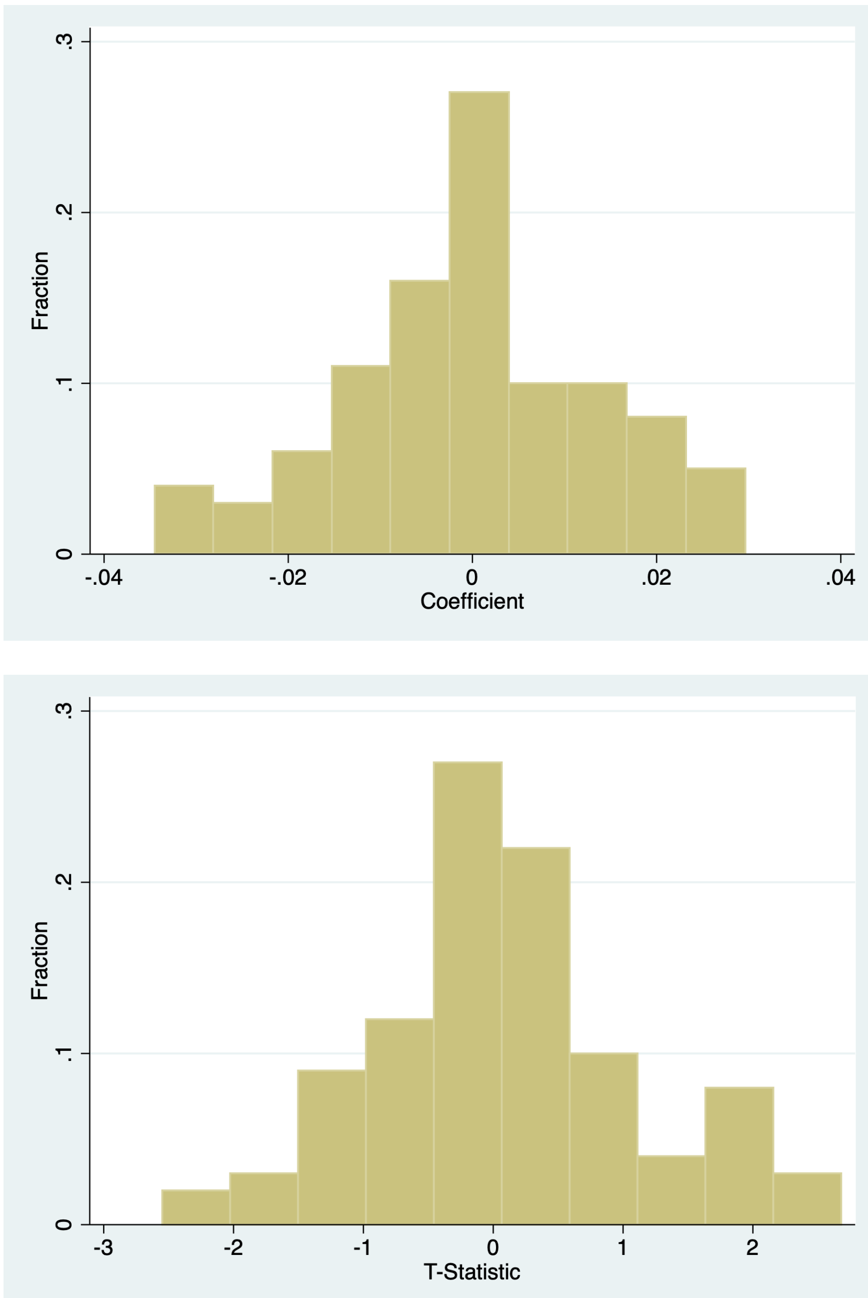


Figure A3. Difference in the speed of effect of deputization by average size of registered investment advisers in a county

This figure estimates the difference in the speed of the effect, between small and large registered investment advisers, of deputizing financial professionals to fight elder financial exploitation around the time of deputization. The red vertical line at month zero indicates the month of treatment. The outcome variable is *Ln(1+# Elder Financial Exploitation Cases)*, the natural logarithm of one plus the number of elder financial exploitation cases in a county-quarter. The coefficients plotted are those on indicator variables indicating the event time *interacted* with whether an indicator for whether the RIAs in a county are greater than one standard deviation above average. The included controls are those in Table 4. Year-month and county fixed effects are included. 90% confidence intervals based on standard errors double clustered at the state and month levels.

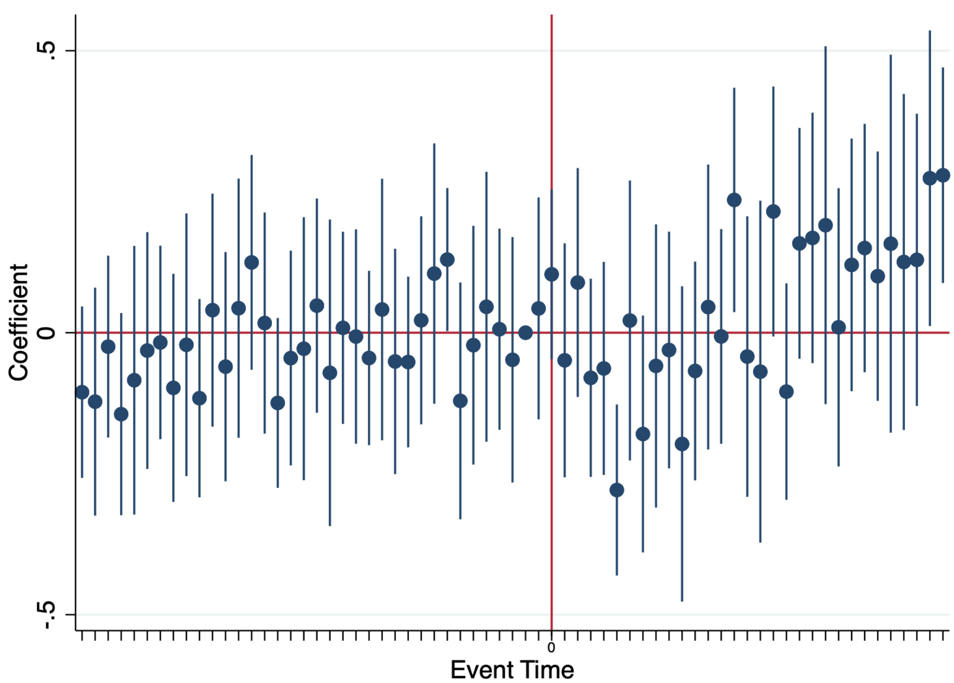


TABLE A1. Correlations

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 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						
	(0.062)						
Fraction of Population 65+		0.069					
		(0.504)					
Average Household Income			0.108				
			(0.125)				
Average Credit Score				0.031			
				(0.054)			
Fraction Married					0.092		
					(0.247)		
Fraction Male						0.173	
						(1.103)	
Log State Population							-0.120
							(1.286)
R^2	0.00	0.00	0.03	0.01	0.01	0.00	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	0.003						
	(0.005)						
Fraction of Population 65+		-0.043					
		(0.029)					
Average Household Income			-0.012				
			(0.008)				
Average Credit Score				-0.004			
				(0.004)			
Fraction Married					0.013		
					(0.015)		
Fraction Male						-0.024	
						(0.065)	
Log State Population							-0.074
							(0.074)
R^2	0.01	0.04	0.04	0.03	0.01	0.00	0.02
# States	51	51	51	51	51	51	51

TABLE A3. Hazard Model of States' Adoption

The table below reports the coefficients from a Weibull hazard model. We follow Acharya et al. (2013). The "failure event" is the first month in which a state adopted policies that deputized financial professionals. States are dropped from the sample once they deputize financial professionals. The explanatory variables (all lagged by one year) are described in Table 3. Robust standard errors (clustered by month) are given in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Ln(1+Elder Financial Exploitation Cases)	0.001										
	(0.003)										
Log Population Above 65		0.004									
		(0.006)									
Vantage Score			0.012								
			(0.014)								
Fraction of Subprime				-0.013							
				(0.014)							
Fraction of Low Income					-0.016						
					(0.017)						
Average Age						0.016					
						(0.019)					
Fraction of Male							0.005				
							(0.011)				
Married								0.000			
								(0.003)			
Household Income									0.009		
									(0.012)		
Household Debt-to-Income Ratio										-0.028	
										(0.026)	
Bachelor or Higher											0.007
											(0.010)
Constant	4.272***	4.230***	4.275***	4.274***	4.275***	4.276***	4.279***	4.279***	4.275***	4.284***	4.277***
	(0.043)	(0.040)	(0.045)	(0.044)	(0.044)	(0.046)	(0.049)	(0.049)	(0.044)	(0.053)	(0.046)
ln_p	3.306***	3.241***	3.246***	3.245***	3.234***	3.247***	3.241***	3.240***	3.244***	3.239***	3.242***
	(0.570)	(0.569)	(0.563)	(0.563)	(0.560)	(0.566)	(0.569)	(0.570)	(0.565)	(0.562)	(0.568)

TABLE A4. Growth in Reporting from 2012 to 2016 and Timing of Model Act Adoption

This table examines whether the change in reporting of elder abuse cases at the state level is related to the timing of adoption of the Model Act. *% Δ Elder Financial Exploitation Cases (2012 to 2016)* is the growth in elder abuse cases in a state from 2012 to 2016. In Column (1), if a state has not adopted the Model Act by the end of the sample (December 2019), then we assume the state adopted the Model Act in December 2019. In Column (2), only states that adopted the Model Act in the sample period are included. Robust standard errors reported. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Months until State Adopts Model Act	
	(1)	(2)
% Δ Elder Financial Exploitation Cases (2012 to 2016)	-1.044	7.496
	(4.167)	(6.007)
Adjusted R^2	-0.02	0.02
Observations	49	24

TABLE A5. Effects of Deputization on Elder Financial Exploitation for Different Sample Periods

For different start years, this table presents difference-in-differences estimates of the effect of the deputizing financial professionals on elder financial exploitation. The outcome variable 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 empowered to reach out to trusted contacts and halt suspicious transactions because a state adopts the Model Act. The controls are those in Table 4. 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	-0.084**	-0.074**	-0.063**	-0.053**	-0.039*
	(0.032)	(0.029)	(0.025)	(0.022)	(0.020)
Constant	0.251***	0.256***	0.267***	0.284***	0.301***
	(0.005)	(0.006)	(0.009)	(0.013)	(0.020)
Controls	Yes	Yes	Yes	Yes	Yes
Sample Years	All	>2012	>2013	>2014	>2015
Year-Month FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.52	0.56	0.59	0.60	0.61
# Counties	3139	3139	3139	3139	3139
Observations	291927	263676	226008	188340	150672

TABLE A6. Effects of Deputization on Elder Financial Exploitation before FINRA Rules 2165 and 4512

This table presents difference-in-differences estimates of the effect of 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 the Model Act becomes effective in a state. 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 3. 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	-0.046	-0.043	-0.056**	-0.050*
	(0.061)	(0.028)	(0.027)	(0.025)
Log Pop Above 65		0.231***	0.246***	2.485***
		(0.025)	(0.026)	(0.348)
Vantage Score (65+)		-0.076***	-0.055***	-0.024***
		(0.014)	(0.010)	(0.007)
Fraction of Subprime (65+)		-0.021***	-0.014**	-0.016***
		(0.006)	(0.005)	(0.004)
Fraction of Low Income (65+)		0.012	0.017***	0.011**
		(0.007)	(0.006)	(0.005)
Average Age (65+)		-0.007	-0.013**	-0.011**
		(0.006)	(0.006)	(0.005)
Fraction of Male (65+)		-0.004	-0.006**	-0.005
		(0.003)	(0.003)	(0.003)
Fraction of Married (65+)		-0.004	-0.012***	0.005
		(0.005)	(0.004)	(0.004)
Household Income (65+)		0.041***	0.025***	0.024***
		(0.013)	(0.009)	(0.008)
Household Debt-to-Income Ratio (65+)		-0.014***	-0.019***	-0.002
		(0.005)	(0.005)	(0.003)
Bachelor or Higher (65+)		0.081***	0.076***	0.058***
		(0.011)	(0.012)	(0.021)
Constant	0.185***	0.187***	0.189***	0.224***
	(0.022)	(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	0.05	0.31	0.33	0.49
# Counties	3139	3139	3139	3139
Observations	219730	219730	219730	219730

TABLE A7. 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. *Post* is an indicator variable that equals to one after the Model Act becomes effective in a state. The controls are listed in Table 4. 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	-0.008	-0.001
	(0.005)	(0.002)
Log Population Above 65	0.165*	-0.021
	(0.087)	(0.034)
Vantage Score (65+)	-0.004***	-0.001**
	(0.001)	(0.000)
Fraction Subprime (65+)	-0.003***	-0.001**
	(0.001)	(0.000)
Fraction Low Income (65+)	0.003**	0.000
	(0.001)	(0.000)
Average Age (65+)	-0.005***	-0.002***
	(0.001)	(0.001)
Fraction Male (65+)	-0.001***	-0.000***
	(0.000)	(0.000)
Fraction Married (65+)	0.000	0.000
	(0.001)	(0.000)
Household Income (65+)	0.008***	0.002**
	(0.003)	(0.001)
Household Debt-to-Income Ratio (65+)	-0.000	-0.001**
	(0.001)	(0.000)
Bachelor or Higher (65+)	0.009**	0.001
	(0.004)	(0.001)
Constant	0.029***	0.008***
	(0.002)	(0.000)
Year-Month FE	Yes	Yes
County FE	Yes	Yes
Adjusted R^2	0.26	0.42
# Counties	3139	3139
Observations	291927	291927

TABLE A8. Effects of Deputization on Elder Financial Exploitation (State-Month Panel)

Collapsing the data by state-month, this table presents difference-in-differences estimates of the effect of the deputizing financial professionals on elder financial exploitation. *Post* is an indicator variable that equals to one after financial professionals are first empowered to reach out to trusted contacts and halt suspicious disbursements because a state adopts the Model Act. The outcome in column (1) is the log of the number of elder financial exploitation cases in a county-year. Column (2) is the number of cases. The outcome in Column (3) is the number of cases per 100,000 persons of 65 years of age or older, and column (4) is the log of the number of cases per 100,000 persons of 65 years of age or older. The controls are listed in Table 4. To generate state-level controls from county-level variables, we take the population-weighted average in a state in a year. Standard errors, double-clustered by state and month, are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	X = Elder Financial Exploitation Cases			
	Ln(1+X)	X	X/Pop.	Ln(1+X/Pop.)
	(1)	(2)	(3)	(4)
Post	-0.056	-40.114*	-1.570*	-0.056
	(0.068)	(21.947)	(0.879)	(0.060)
Constant	3.625***	89.503*	8.267***	1.958***
	(0.230)	(52.226)	(2.991)	(0.206)
Controls	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.87	0.74	0.74	0.68
# States	51	51	51	51
Observations	3012	3012	3012	3012

TABLE A9. Effects of Deputization on Elder Financial Exploitation (County-Year Panel)

This table presents difference-in-differences estimates of the effect of the deputizing financial professionals on elder financial exploitation. The sample is a county-year panel. We discard counties with zero reports in the full sample. We also restrict the sample period to 2014 to 2019 (omitting the first years of high growth in reporting). In this revised sample, only 30% of county-year observations are zeros. The formulation of the outcome variable varies. The outcome in column (1) is the log of the number of elder financial exploitation cases in a county-year. Column (2) is an indicator variable that equals to one if a county-year has above zero elder financial exploitation cases. Column (3) is the number of cases. The outcome in Column (4) is the number of cases per 100,000 persons of 65 years of age or older, and column (5) is the log of the number of cases per 100,000 persons of 65 years of age or older. *Post* is the proportion of months in a year that financial professionals are empowered to reach out to trusted contacts and halt suspicious disbursements because a state adopts the Model Act. A detailed description of the control variables can be found in Table 3'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.

	X = Elder Financial Exploitation Cases			
	Ln(1+X)	X	X/Pop.	Ln(1+X/Pop.)
	(1)	(2)	(3)	(4)
Post	-0.136**	-13.909*	-0.429	-0.112*
	(0.049)	(6.716)	(0.674)	(0.045)
Constant	1.531***	20.561***	6.241***	1.339***
	(0.009)	(0.741)	(0.160)	(0.010)
Controls	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.79	0.58	0.42	0.41
# Counties	2608	2608	2608	2608
Observations	15648	15648	15648	15648

TABLE A10. Elder Financial Exploitation by Per Capita Investment Advisers

Per Capita Investment Advisers (Brokers) is a county's per capita number of investment advisers (brokers). The control variables are listed in Table 4. 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)
Per Capita Investment Advisers	0.040***		0.002
	(0.012)		(0.015)
Per Capita Brokers		0.052***	0.051**
		(0.015)	(0.020)
Controls	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
County FE	No	No	No
Adjusted R^2	0.37	0.38	0.38
# Counties	2557	2557	2557
Observations	225016	225016	225016

TABLE A11. Effects of Deputization on Elder Financial Exploitation by RIA Size

This table presents the difference-in-differences estimates of the effect of the deputizing financial professionals on elder financial exploitation by RIA size. *Post* is an indicator variable that equals to one after financial professionals are first empowered to reach out to trusted contacts and halt suspicious disbursements because a state adopts the Model Act. *RIA Size* is the average AUM of the RIAs advisers work at in a county. *Per Capita Investment Advisers* is a county's per capita number of investment advisers. *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. The controls are listed in Table 4. 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)
Post	-0.027	-0.060***
	(0.028)	(0.018)
Post × RIA Size	-0.089***	-0.007
	(0.019)	(0.020)
Post × Per Capita Investment Advisers		-0.053*
		(0.028)
Post × Time in County		-0.019*
		(0.010)
Post × Time in Profession		-0.009
		(0.011)
Interacted Controls	Yes	Yes
Year-Month FE	Yes	Yes
County FE	Yes	Yes
Adjusted R^2	0.56	0.60
# Counties	3139	3139
Observations	291927	291927

TABLE A12. Drop in Elder Financial Exploitation by Number of State Registrations of Advisers

This table presents the difference-in-differences estimates of the effect of the deputizing financial professionals on elder financial exploitation. *Model Act Adopted Before FINRA* is an indicator variable that equals to one if a state adopts the Model Act before the FINRA rule change in February 2018. *Model Act Adopted After FINRA* is an indicator variable that equals to one if a state adopts the Model Act after the FINRA rule change in February 2018. *No. State Registrations per Adviser* is the average number of state registrations per adviser. A detailed description of the control variables can be found in Table 3'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.

	Ln(1+Elder Financial Exploitation Cases)
	(1)
Model Act Adopted Before FINRA	-0.081**
	(0.032)
Model Act Adopted Before FINRA × No. State Registrations per Adviser	-0.010
	(0.023)
Model Act Adopted After FINRA	-0.101**
	(0.048)
Model Act Adopted After FINRA × No. State Registrations per Adviser	0.020
	(0.026)
Interacted Controls	Yes
Year-Month FE	Yes
County FE	Yes
Adjusted R^2	0.52
# Counties	3139
Observations	291927

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-differences 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-differences 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-differences estimator is a weighted average of all possible two-group/two-period difference-in-differences 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.

Table A13 shows the results of the Goodman-Bacon (2018) decomposition.[51] 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 -0.024 and has a weight of 16.4%. 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 0.004 and has a weight of 5.2%. 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 third component is "Treated vs Never Treated", which compares states that adopted the policy at some point during the sample period and those that did not. The average estimate derived from this source of variation is -0.087 and has a weight of 76.4%. The last component is "Treated vs Already Treated", which compares states that are treated during the sample period with states that are always treated during our sample period (Washington state). The average coefficient estimate derived from this source of variation is -0.200 and has a weight of 1.9%.

[51] 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.

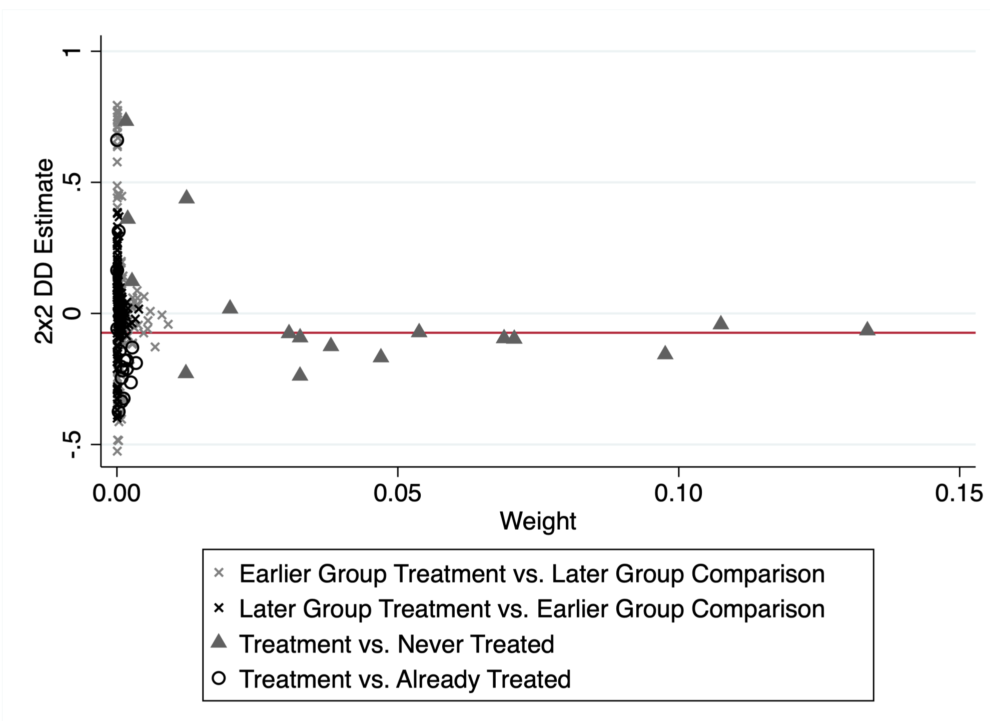
TABLE A13. Goodman-Bacon Decomposition

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 4 Panel A Column (6).

Variation	**Beta**	**Weight**
Earlier Treated vs Later Control	-0.024	0.164
Later Treated vs Earlier Control	0.004	0.052
Treated vs Never Treated	-0.087	0.764
Treated vs Already Treated	-0.200	0.019

Figure A4. 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 A13.



Appendix C. Factiva Searches

TABLE A14. 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