Deputizing Financial Institutions to Fight Elder Abuse

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Abstract

Elder financial abuse is a pervasive and growing problem that results in billions of financial losses annually. To help, regulators deputized financial professionals, permitting them to reach out to trusted contacts and to halt suspicious disbursements of funds. Exploiting variation in the adoption of such laws, we find that elder financial abuse dropped in treated counties by 0.3 (0.6) cases per month, or 7% (15%) of a standard deviation, by the second (fourth) year following implementation. The effect is stronger where elderly are more isolated. Our results highlight the role of the financial industry in combating social problems.

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1. Introduction

Elder financial exploitation is a pervasive and growing problem. 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, involving $1.7 billion in losses (CFBP, 2019). DeLiema et al. (2020) find that 8.7% of older Americans were victims of fraud in the past five years. This issue will likely become more prevalent as the elderly population grows from 15.2% to 23.4% of the total population in the next 40 years (Vespa, 2018). Elder abuse is also difficult to police. The perpetrators are often people close to the victim like family members and caregivers.

To combat elder financial abuse, regulators deputized financial professionals, granting them two new authorities. The first is the authority to reach out to a trusted contact to discuss red flags and confirm mental and physical health status. The second is the authority to halt the disbursement of funds that appear suspicious for financial abuse. These new rules are permissive rather than mandatory. Regulators do not give financial professionals explicit financial rewards for acting and do not subject professionals to punitive actions if they choose not to act.

Are financial professionals effective monitors, and what is the economic and social value of deputizing people in the financial industry? Financial professionals are often called upon to monitor for crimes and misbehavior in societies (e.g., money laundering, terrorism financing, and fraud). However, little is known in the literature about their effectiveness, and whether this aspect represents an important contribution of finance to societies, because large-scale, quasi-natural experiments are rare(Zingales, 2015). Such monitoring tasks are often so challenging that financial professionals are not culpable for failing to detect these crimes. The scale of the tasks also makes it infeasible for the regulators to reward completely the agents who act and to punish those who do not.

We answer these questions in the setting of fighting elder financial abuse. Our setting provides an opportunity to estimate the effectiveness of financial professionals as monitors in societies, as state regulators rolled out the two new authorities to curb elder abuse in a staggered fashion. In 2016, the North American Securities Administrators Association (NASAA) passed the *NASAA Model Legislation or Regulation to Protect Vulnerable Adults from Financial Exploitation* (hereinafter, "Model Act"). By 2020, thirty states have adopted the Model Act provisions. In most states, these provisions apply to investment advisers and broker-dealers. In five states, the laws apply to all financial professionals (including all bank employees).

Anecdotal evidence suggests that the two new authorities are helpful at curbing abuse. Prior to the Model Act, strict privacy laws impeded advisers' efforts to consult with trusted contacts of their clients in suspicious cases (Berdychowski, 2019). Now, professionals may tell the trusted contact that "staff have reason to believe that the account holder may be the current target of a scam—you might want to speak to the account holder to see if he or she will give details to aid you in providing helpful advice" (NAFCU, 2020). The ability to halt disbursement of funds is often a useful last resort. The head of Alabama's securities division informed us 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.

This setting is natural for a dynamic, staggered difference-in-differences (DiD) specification

(Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021). Our identifying assumption 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. We show that whether and when a state deputizes financial professionals is unrelated to a state's previous financial exploitation cases, the size of the elderly population, and other observable characteristics. Our dynamic specification always reports the pre-adoption event time estimates to gauge whether pre-trends are parallel. We conduct the Goodman-Bacon (2021) and Callaway and Sant'Anna (2021) decomposition to analyze sources of variations that contribute to our estimates. We also conduct a minimum distance matching to align the treated and control counties in observable aspects.

We amass a large dataset: detailed county-month reports of elder financial exploitation from the Department of Treasury, the employment history of the entire universe of registered brokers and investment advisers from Financial Industry Regulatory Authority (FINRA) and the Securities and Exchange Commission (SEC), county-level data about the elderly's demographic and economic characteristics from the U.S. Census Bureau and Experian, social connectedness measures from Facebook and the U.S. Religion Census, and social capital measures from the U.S. Joint Economic Committee.

The dependent variable that we analyze is the county-level, monthly counts of elder abuse cases, 80% of which result in an actual financial loss (CFBP, 2019). Alternatively, one could imagine using the incidence of trusted contacts or halted disbursements to study the effectiveness of the new regulation. This may not be ideal for two reasons. First, an analysis of these actions may mischaracterize the effectiveness of deputization because they can interact with other hidden actions that help curb abuse. For example, financial professionals may deter exploitation when they roll out a trusted contact system, preventing abuse before it is attempted, and thus eliminating the need to make reports to regulators. Second, data on contacting trusted parties and halting disbursements are fraught with errors because documentation is often incomplete or unavailable.[1] So, the observable equilibrium outcome that best captures the deterrent role of deputization is the ultimate frequency of elder abuse cases.

If deputization is effective, we expect a drop in reported cases 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 to the Department of Treasury 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

[1] In discussions with FINRA and NASAA, it is not standard practice to document these actions in case records, and even if the documentations existed, they may not be shared externally due to privacy agreements. We performed a case-study analysis in conjunction with the Texas Adult Protective Services, and found that investigations initiated in response to validated reports from financial institutions did include information about delayed disbursements in a few occasions. However, 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. Furthermore, the data cannot be shared systematically with researchers.

attempting abuse. Relatedly, as the deputies take their role seriously and set up trusted contact systems and procedures for halting disbursements, their actions can act as a deterrent.

We find that deputizing appears to be effective at deterring the financial exploitation of the elderly. We estimate that this policy led to a reduction in the monthly number of elder financial abuse cases in treated counties by 0.3 (0.6) cases per month, or 7% (15%) of a standard deviation, by the second (fourth) year. A log specification indicates a drop in abuse of about 3.4% (10.0%) by the second (fourth) year. We find similar drops using the per capita number of abuse cases as the outcome and when estimating a Poisson model (Cohn et al., 2021). Consistent with a state's adoption being quasi-random, in advance of a state's adoption, we find no evidence of differential trends in elder abuse for treated and control counties.

The effect is non-immediate as it takes time for regulators to host information sessions, for financial firms to train their professionals, for financial firms to put systems in place (getting clients to provide trusted contacts), and for perpetrators to learn about the new safeguards. Because the effect is non-immediate, it is important to decompose our estimator using the Goodman-Bacon (2021) approach, as the estimator partially stems from comparing abuse in counties treated at different times, which can be problematic when the effect is not immediate. The decomposition shows that our model puts a weight of about 75% on the cleanest comparison of treated counties and never-treated counties. We obtain similar results using the Callaway and Sant'Anna (2021) DiD estimation, which forces the control counties to be never treated counties.

Several tests link the drop in elder abuse directly to the channels of the policy. First, the effect is stronger in counties with more deputies (i.e. advisers and brokers) per capita, controlling for variation in the effect with other county covariates such as income and education (Yzerbyt et al., 2004). Relatedly, there is no drop in counties with zero deputies. Second, consistent with the focus on disrupting disbursements of funds, our results are more significant when we focus on abuse involving fund transfers. Relatedly, we find a drop in abuse involving fund transfers controlling for less-affected types of elder financial exploitation in the same county-month, such as abuse involving mutual funds (transactions not protected, only disbursements), home equity lines of credit (subject to rigorous closing process), and credit cards. Third, there is no drop in reports of abuse from money services businesses, which do not employ brokers and advisers. Fourth, there is no drop in suspicious activity reports unrelated to elder financial abuse (e.g., reports on insider trading), suggesting no systematic change in reporting behaviors by financial institutions.

We conduct a series of additional robustness tests to rule out alternative explanations. The drop is robust to including county and month fixed effects and time-varying county controls, to removing county-specific linear trends in abuse as advised by Goodman-Bacon (2021), to dropping any state, to matching counties on pre-treatment characteristics, to state-level aggregation of the data, and to narrowing the sample period around the event date.

Several pieces of evidence suggest that brokers appear to be less effective deputies than investment advisers. First, when we horse race the county per capita number of brokers and advisers in the same regression, we find that the drop in abuse is only significantly related to the presence of advisers. An important caveat is that these measures are highly correlated because 85% of advisers are dual-registered as brokers. Second, we find less evidence of a drop in elder abuse reports from pure broker-dealer institutions; however, there are fewer such reports in general because broker-dealers are often housed inside larger financial institutions. Third, the effectiveness of the Model Act provisions does not drop after a rule change by FINRA granting the same authorities to brokers nationwide in 2018. If brokers were effective deputies, then we'd expect that the Model Act become less effective after brokers are already deputized nationwide. Collectively, 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.

Within the set of investment advisers, there is heterogeneity in their effectiveness as deputies. There is a larger drop in abuse when investment advisers serve wealthier clients. This may be because those clients provide more fee revenues and are more closely monitored by the advisers. However, we also find that the effect is not related to advisers' compensation arrangements, such as whether advisers charge one-off commissions, fixed fees, or hourly fees, which is less consistent with a fee motivation for acting. Alternatively, it could be the case that advisers serving wealthier clients provide higher-touch services and are thereby more likely to know their clients better and thus what is suspicious. The effect may also be larger for advisers serving wealthier clients because abuse against wealthier clients is more likely to have exceeded the $5,000 threshold, above which reporting is mandatory.

Because it is well known that social isolation is a leading risk factor for abuse (Podnieks, 1992; Choi et al., 1999; Bernatz et al., 2001), we examine whether the effect of deputization varies with a county's social connectedness. Strengthening the ability of financial professionals to interrupt abuse appears to be more effective for socially isolated elderly persons, measured using the Facebook social connectedness index and the number of religious congregations per capita (Alves and Wilson, 2008; Lichtenberg et al., 2013; James et al., 2014; Lichtenberg et al., 2016; DeLiema, 2018). Relatedly, the effect is stronger in less cooperative communities with a lower social capital index score.

Finally, it is possible that the magnitudes of the effects of deputization in this paper underestimate the potential role of deputization in other settings. First, we cannot observe the drop in attempted abuse that exceeds the $5,000 mandatory reporting threshold but is later interrupted. Second, a growing literature documents that some financial professionals engage in frequent misconduct and even prey on the elderly themselves (e.g. Dimmock and Gerken, 2012; Dimmock, Gerken, and Graham, 2018; Charoenwong, Kwan, and Umar, 2019; Egan, Matvos, and Seru, 2019). Thus, it is reasonable to expect that deputies in an industry with less misconduct may be even more effective. Luckily, we find no evidence that financial professionals use their new authorities to abuse the elderly, as there is no evidence of an increase in regulatory actions against advisers. In general, a large literature examines and reveals the misconduct of financial professionals. We are one of the few papers that examine the ability of financial professionals to prevent financial fraud, which represent an important contribution of finance to societies.

2. Background

2.1. Elder Financial Exploitation

Elder financial exploitation, or elder financial abuse, is defined by the U.S. Government Accountability Office as the "illegal or improper use of an older adult's funds, property, or assets" (GAO, 2011). Such exploitation is pervasive and economically costly. In 2017, there were 63,500 cases of elder financial exploitation reported to the Department of the Treasury, involving $1.7 billion in losses (CFBP, 2019). This issue will likely become more prevalent as the elderly population grows in the next 40 years (Vespa, 2018).

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 (ALZ, 2019).

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 (DOJ, 2018). Their wealth, combined with greater financial autonomy upon retirement brought by a general shift from defined benefit to defined contribution plans, makes them popular targets of financial exploitation.

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.

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 the United States. In addition, several studies examine elder abuse cases across different demographic groups and find mixed results. DeLiema et al. (2012) find that low-income Hispanic immigrants are disproportionally victimized, whereas DeLiema et al. (2020) do not find higher incidence of abuse against females or Hispanics.

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. 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, and SEC-registered investment advisers manage about 25% of global wealth.[2]

About 85% of investment adviser representatives are also registered as brokers. The reverse is not true—only about 50% of broker representatives are dual-registered as investment advisers. Both broker-dealers and investment advisers could be employees of large financial institutions, such as bank holding companies. Below we provide a more detailed description of these deputies.

2.2.1. Investment Advisers

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, managing clients' wealth, and constructing personalized financial plans. These plans may include not only investments but also savings, budget, insurance, and tax strategies. 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). 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.

2.2.2. Broker-dealers

FINRA oversees broker-dealers, which employ brokers. The Securities Exchange Act of 1934 defines a broker-dealer as any "company engaged in the business of buying and selling securities on behalf of its clients, for its own account (as dealer), or both." Broker-dealers may be standalone securities 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

[2]According to sources in Bureau of Labor Statistics, Investment Adviser Public Disclosure (IAPD), and BrokerCheck, 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 (350,731+701,181-298,181)/8,203,000 = 9.5% of the finance industry . In addition, as of 2014, investment adviser firms registered with the SEC reported managing approximately $61.9 trillion in assets for their clients, and total global wealth in 2014 is estimated to be $251 trillion . See https://www.govinfo.gov/content/pkg/FR-2015-09-01/pdf/2015-21318.pdf and https://onlinelibrary.wiley.com/doi/full/10.1111/roiw.12318.

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

There are 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) rather than mandatory, and do not provide explicit incentives. Before these rules were passed, professionals were already 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.[3] The two rules vary in the types of financial professionals covered and certain other terms of implementation. We summarize these differences in Table 1 and in detailed below.

[Insert Table 1 Here]

3.1. The Model Act

The Model Act originated as an initiative of the NASAA's Committee on Senior Issues and Diminished Capacity. On September 29, 2015, a draft of the Model Act was released for a 30-day public comment period. On January 22, 2016, NASAA members voted to approve the Model Act. By the end of 2020, 30 states had adopted provisions similar to the Model Act in a staggered fashion.

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 are the authority to reach out to a specified trusted contact and the authority to delay disbursements of funds.

Prior to the Model Act, strict privacy laws impeded advisers' efforts to consult with trusted contacts of their clients in suspicious cases (Berdychowski, 2019). Now, professionals may make statements like "staff have reason to believe that the account holder may be the current target of a scam — you might want to speak to the account holder to see if he or she will give details to aid you in providing helpful advice" (NAFCU, 2020). The trusted contact authority is distinct from a power of attorney, which requires elderly to cede control over their finances. Because the deputizing policies are permissive, there is also never any obligation for the financial professionals to reach out to a trusted contact even after the rule (for example, if the financial professional believes the trusted contact to be the perpetrator).

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

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

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. The ability to delay a disbursement of funds allows for an investigation to occur prior to any loss of funds due to exploitation. The head of Alabama's securities division informed us 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.

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

[Insert Figure 1 Here]

As shown in Table 2, as of December 2020, twenty-seven states have enacted legislation that contains many of the provisions found in the Model Act between 2016 and 2020. Prior to the passage of the Model Act in 2016, three additional states—Delaware, Missouri, and Washington —already enacted laws that contain provisions similar to the Model Act. Thus, there are thirty states with provisions similar to the Model Act.

[Insert Table 2 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 (DE, KY, TX, VA, and WA) and two states limited the scope to include only broker-dealers (MO and RI).

3.2. FINRA Rules 2165 and 4512

State regulation of broker-dealers exists in parallel with regulations of 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. The latter rule is permissive rather than mandatory. As FINRA states in its regulatory notice: "The rule creates no obligation to withhold a disbursement of funds or securities in [suspicious] circumstances." Upon placing a hold, FINRA Rule 2165 requires the broker-dealer to immediately initiate an internal review of the facts and circumstances.

To summarize, 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 as opposed to a broader range of financial professionals and is implemented nationally.

4. Data and Sample

4.1. Elder Financial Exploitation

We obtained data on elder financial exploitation from the Suspicious Activity Reports maintained by the U.S. Department of Treasury's Financial Crimes Enforcement Network (FinCEN). As established by the federal Bank Secrecy Act of 1970, financial institutions including 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. Violations of Bank Secrecy Act provisions can result in criminal penalties. Apart from these mandated institutions, as of December 2002, rule 31 CFR § 1023.320 also requires reporting by standalone broker-dealer firms (not a subsidiary of any bank holding companies, which are required to report already). In 2015, it was proposed that standalone investment advisery firms 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 such 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. Important to our empirical design, these reporting requirements to FinCEN by 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 and the financial product involved (e.g. fund transfer). Reports are tied to the county in which the victim resides.[4]

Figure 2 shows the trend in reported abuse. Because there is a large increase in total reports of elder abuse in the months immediately following the reporting category's introduction in 2012, we start the sample in January 2014 (as indicated by the red vertical line). We show that time fixed effects address this remaining aggregate increase in reports after 2014. In Figure 3, we remove the

[4] According to FinCEN, counties are defined by zip codes as provided by the filing institution indicating where the suspicious activity occurred.

national trend in reported abuse and plot the remaining trend across states till June 2016, which is just before the Model Act becomes effective in the earliest adopting states. We find no differential remaining trends for any states.

[Insert Figure 2 Here]

Our results are robust to varying the sample start year or sample end year (Internet Appendix Table A6 and A7). In our main specifications, we also estimate and control for county-level linear pre-trends. However, this common robustness test is ultimately not important for our results, as Internet Appendix Figure A1 repeats Figure 3 without controlling for linear trends, and again shows no evidence of linear pre-trends.[5] Finally, Internet Appendix Table A5 finds no evidence that the growth in reporting at the state-level between 2012 and 2016 is correlated with when states adopt the Model Act provisions.

[Insert Figure 3 Here]

Reporting suspicious activity is mandatory when a suspicious transaction involves at least $5,000 in funds or assets. If such a suspicious disbursement is attempted or occurs, then it must be reported. The rule changes we examine provide financial professionals with new tools to deter attempted abuse. Reports would fall if abuse is interrupted earlier, before reaching the $5,000 reporting threshold. Family members could 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 any regulatory action taken against an adviser.

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,

[5] The level differences in Internet Appendix Figure A1 are a result of states being difference sizes. The linear pretrends remove these level differences, centering states at 0.

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 dual-registered as brokers.

4.3. Social Connectedness Measures

4.3.1. 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, $FacebookUsers_i$ and $FacebookUsers_j$ 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.

4.3.2. 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. These proxies for religiosity are standard in the literature (e.g. Hout and Greeley, 1998; Grullon et al., 2009). 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. 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.

4.3.3. Social Capital Index

We obtained county-level Social Capital Composite Index developed by the Social Capital Project from the U.S. Joint Economic Committee. This index captures information on volunteering, public meeting attendance, non-profit organization participation, and more. This composite index is constructed from four sub-indexes at county level: a family unity subindex, a community health subinex, a institutional health subindex, and a collective efficacy subindex. We use a version of this index released in April 11, 2018.[6]

4.4. Control Variables

We use data on counties from the U.S. Census Bureau as control variables. These data include the number of persons 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 1% 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.

4.5. Summary Statistics

Our sample includes monthly observations for 3,139 counties from January 2014 to December 2020, resulting in 263,676 total county-month 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 1.3, with a standard deviation of 4.1. Because aggregate reports of elder abuse are increasing during our sample period (see Section 4.1 for a discussion), by the end of our sample, the average cases in a county-month is 2.4, with a standard deviation of 5.9. Approximately 80% of county-months have zero reported cases. The 99th percentile of reported senior financial fraud in a county-month is 29. The per capita number of abuse cases is on average 6.4 per 100,000 persons 65 years of age or older, and the 90th percentile is 16.9 cases per 100,000 elderly persons. This rate of elder financial exploitation is similar to the rate of gun deaths, and twenty times more frequent than voter fraud.[7] We winsorize these variables at the 1^{st} and 99^{th} percentile in all OLS specifications to reduce skewness and alleviate the influence of outliers.

[6] The data is downloaded here: https://www.lee.senate.gov/scp-index.

[7] 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. A Brennan Center for Justice report pegs the rate at 0.0003%. The equivalent measure of elder financial exploitation is 0.0064% (6.4/100,000 $\times$ 100), or ten times more frequent. See https://www.brennancenter.org/sites/default/files/2019-08/Report_Truth-About-Voter-Fraud.pdf

[Insert Table 3 Here]

In terms of access to financial professionals, the average number of investment advisers (brokers) per 1,000 individuals is 0.5 (0.8). There is a large distribution in access to financial professionals as the standard deviations of these variables are at least twice as large as their means.

In an average county, roughly 18% of the population is 65 years of age or older. This statistic varies substantially across counties as the standard deviation is 4.6%. In terms of the economic conditions, the counties average about ninety-thousand dollars in household income and about twenty-two thousand dollars in retirement income. The average credit score is about 725. About 19% of the elderly population is subprime on average (credit score below 660) and have an average debt-to-income ratio of approximately 6.5%.

5. Results

5.1. Empirical Specification

We employ a generalized DiD 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, in our main specifications, we exploit differences across states in the timing of passage of the NASAA Model Act. Later, we also examine the Model Act's interaction with the FINRA Rules 2165 and 4512, which are directed at brokers only and apply nationally.

Table 2 and Figure 1 show variations in the treatment dates across states. We estimate models of the following two forms:

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

and

$$OUTCOME_{ct} = \alpha + \beta \mathbb{1}(t - \text{Treatment Date}_s = h) + \gamma' \mathbf{X}_{ct} + \eta_c + \eta_t + \epsilon_{ct} \tag{3}$$

Here, we index county by c, state by s, and month by t. In Equation 2, $POST_{st}$ 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. The β on $POST_{st}$ measures the static effect of deputization. $\mathbf{X}_{ct}$ denotes a vector of time-varying county demographic and economic 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 and detailed in Footnote 8.[8] We include county fixed effects, denoted by η_c, to absorb any unobserved persistent county

[8] Here is the list of county-year controls and reasoning:

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.

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). For additional robustness, we also estimate and control for county-level linear trends in elder abuse, estimated during the pretreatment period and projected forward through the treatment period per Goodman-Bacon (2021). We cluster standard errors at the state level, because Bertrand et al. (2004) recommends clustering at the state level in DiD models with state-level treatment to account for serial-correlation. Bertrand et al. (2004) writes, "This technique works well when the number of groups is large (e.g., 50 states) but fares more poorly as the number of groups gets small." Our sample overs all 50 states and the District of Columbia.

In Equation 3, we show the dynamics of the DiD coefficients as Goodman-Bacon (2021) cautions against only relying on a "single coefficient two-way fixed effects specification to summarize time-varying effects." h is the event time, which is only defined for states treated by December 2020. We estimate these dynamics for the four years before and after the month the policy becomes effective in a state. For compactness in the presentation of our regression tables, when estimating Equation 3, we estimate the effect for the semi-annual (six-month) intervals before and after the month a state adopts the Model Act. In addition, as in Callaway and Sant'Anna (2021), we omit the indicator immediately before a state adopts the Model Act.

5.2. Main Effects

We find that deputizing financial professionals appears to be effective at deterring financial exploitation of the elderly. Table 4 shows the results. In columns (1) to (3), the outcome variable is the count of elder financial exploitation in a county-month. Column (1) shows that the static effect is a 0.186 drop in the number of abuse cases per county-month, which represents 4.5% (0.186/4.1) of a standard deviation change.

[Insert Table 4 Here]

Table 4 Column (2) shows the dynamic effect. A significant decline in abuse is observable after the first year. About two years after the policy implementation in a state, abuse declines by -0.208 cases per county-month. By four years after implementation, the decline is -0.565 cases per county-month. Because we are examining count data, in Column (3), we also examine whether the results hold using a Poisson specification as advised in Cohn et al. (2021). We see a similar decline in elder abuse over time. Column (4) shows a decline when we change the outcome to the natural log of one plus the number of abuse cases to reduce any skewness in the count data. Column (5) also

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.

shows a decline when we change the outcome to the number of elder financial exploitation cases per capita (per 100,000 persons 65 years of age or older). We also find similar and often more significant results when we repeat these same specifications on the subset of abuse involving fund transfers (see Columns (6) to (10)).

To interpret the economic magnitudes, Column (2) coefficients on *Post 6* and *Post 7* indicate a decline of 0.489 and 0.565 cases per county-month. It is more appropriate to compare this effect to the sample mean in later periods rather than the unconditional sample mean. This is because most states are treated in the latter half of the sample (2016-2020), and the coefficients on *Post 6* and *Post 7* are estimated primarily using data from the last six months of 2020 (four years after the first few states are treated in July 2016). Relative to the December 2020 mean, the drop represents a 24% decline in abuse.

We can also interpret the coefficient estimates in other columns and they point to similar economic magnitudes. For example, the magnitude of the coefficient in the natural log specification in Column (4) indicates an about a 10% drop in abuse. However, we caveat that the frequency of zeros in the county-month panel challenge the log of one plus specification and its interpretation as a percentage change. The state-month panel in Internet Appendix A4 largely eliminates the zero observations and shows a drop of about 23% by the fourth year following treatment. If all states were treated, the economic magnitude predicts a monthly reduction of 1,773 cases (0.565×3139) per month across the 3,139 counties in our sample.

To help visualize the results in Table 4, we plot the coefficients of the dynamic specifications in Figure 4. The plots make clear that there is no evidence that treated and control counties have different trends in abuse prior to treatment. Also, the plots show that the effect of the policy is increasing over time.

[Insert Figure 4 Here]

The delay in the effect may occur for a few reasons. First, it takes time for regulators to spread the word through information sessions, for financial firms to develop protocols for implementation, and for firm to provide training. State securities divisions have been organizing seminars for financial professionals to inform them about the rule change. 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. Additionally, 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.

Because we find that the treatment effect is increasing over time, this trend helps rule out the possibility that the policy created an empty threat and deputies did not act at all. In that case, we would likely observe an initial temporary decline caused by the threat of the new regulations, and a subsequent reversal when rational perpetrators would soon learn that financial professionals are not performing as deputies. Instead, we find that the treatment effect persists and increases over time.

5.3. Identification Assumptions and Robustness Tests

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, which are discussed below.

5.3.1. Is policy adoption endogenous?

We explicitly model the policy adoption decisions across states and find that the decision does not seem to be driven by observable state characteristics. In Figure 5, we show graphically that the timing of adoption is unrelated to many key variables, including the rate of elder abuse, the proportion of adults 65 years of age or older, the average income of the elderly, and the population of a state. In Internet Appendix Table A2 Panel A, we confirm this result with regressions and show that adoption is unrelated to additional covariates (average credit score, % of elderly who are subprime, % of elderly who are low income, number of elderly, % of elderly who are male, % of elderly who are married, debt-to-income ratio of the elderly, and educational attainment). Overall, there is no strong relation between a variety of state characteristics and *when* a state adopts the Model Act.

[Insert Figure 5 Here]

The exact timing of adoption in a relatively short time window may plausibly be exogenous because of idiosyncratic conventions by state legislators, which meet at different times of the year and set different effective dates for new laws. Also, state legislators in some states may not be able to fully pass a policy in one year by the end of the legislative session because of unrelated obligations. For instance, in Florida, by September 2019, the bill had passed through Florida's House of Representatives twice, but not Florida's Senate, due to busier than usual legislative sessions (Berdychowski, 2019)

Importantly, as discussed more below, the main variation driving our estimates of the effect comes from comparing treated and never-treated states, so an important consideration is the extensive margin - whether the choice to adopt the policies at all by 2020 is related to variables of interest. Internet Appendix Table A2 Panel B shows no significant relation between many state characteristics and *whether* a state adopts the Model Act provisions by 2020.

5.3.2. Parallel Pre-Trend

Figure 4 shows no unusual changes in elder financial exploitation prior to the rule change, and a noticeable drop only following the rule change. The figure shows evidence of parallel pre-trends using four different specifications. The figure also shows similar evidence using the sub-sample of abuse cases involving fund transfers, which are more targeted by the policy. In Internet Appendix Figure A2, we show similar evidence at the monthly frequency.

5.3.3. Decomposing the Treatment Effects per Goodman-Bacon (2021) and Callaway and Sant'Anna (2021)

To help give more context on the empirical design, we also run the Goodman-Bacon decomposition and analyze the weights underlying our staggered DiD regressions. As Goodman-Bacon (2021) notes, the two-way fixed-effect estimator is a weighted average of all potential 2×2 DiD estimates, where the weights are determined by both the size of the treated group and the timing of the treatment. In running the decomposition, we open the black box of the two-way fixed-effect estimator and dig deeper into the comparisons that contribute to the coefficient in our main table.

Table 5 and Internet Appendix Figure A3 show the results of the decomposition for the static effect estimate in Column (1) of Table 4 of -0.186. Most of the variation used to estimate β results from the cleanest comparison of treated states to never treated states. Specifically, "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 -0.246 and has a weight of 74.4%.

[Insert Table 5 Here]

A heavy weight on the comparison "Treated vs Never Treated" is advantageous, because in the presence of dynamic treatment effects, coefficient estimates could be biased (Goodman-Bacon 2021). For example, comparisons that involve "Early Treated" vs "Later Control" may attenuate the estimated effect, as there could be negative drifts in elder abuse cases for the later treated states after treatment. This drift would bias the coefficient downwards, and the magnitude of the bias depends on the sample period length and the dynamic effects. This reasoning may explain why the effect estimated using these comparisons is only -0.024 cases per county per month. A similar issue arises when comparing the later treated to all previously treated states ("Later Treated" vs "Earlier Control"). When the treated states are used as controls, and to the extent that there are any dynamics in the treatment effects, this will attenuate the estimated coefficient—potentially even flipping the sign of the estimate. Again, this may explain why the effect estimates using these comparisons is positive 0.049 cases per county per month.

Relatedly, we implement the procedure in Callaway and Sant'Anna (2021) to estimate the average treatment effect of the policy in event time only using the never-treated states as control states. Figure 6 shows that for both the total number of elder abuse cases and the number of abuse cases involving fund transfers, there are apparently similar pre-trends between the treated and control states and a divergence after treatment, with abuse cases dropping.

[Insert Figure 6 Here]

That said, using only the never-treated states as controls could potentially bring other concerns. For example, they may be fundamentally different from the treated states. We present evidence alleviating this concern: the adoption model estimated in Internet Appendix Table A2 Panel B shows that the adoption decision is uncorrelated with state economic and demographic characteristics. To further mitigate this concern, we perform a matching procedure to ensure that the treated and control counties are observably similar, and repeat our analysis on the matched sample. We discuss this procedure in detail below.

5.3.4. Matched Sample Analysis

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 4, the parallel trend assumption — that treated and control groups would 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 the vector of control covariates in Footnote 8 and elder abuse, all measured as of December 2015.[9] 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 DiD regressions, including a set of matched-pair fixed effects to ensure that treatment effects are identified from within-pair comparisons. We limit the sample to the 25% of matches with the closest geometric distances. Table 6 Panel A shows that the dynamic estimates using matched county pairs are statistically significant and economically similar to those presented in Table 4 for both total elder abuse cases in a county-month and for abuse involving fund transfers. Table 6 Panel B is a covariate balance table, which shows that paired counties are similar in observable aspects.

[Insert Table 6 Here]

5.3.5. Could differences or changes in reporting drive the results?

The nature of our data is reported elder financial abuse cases, rather than the entire universe of actual elder abuse cases, which is inherently unobservable. In this section, we address several concerns that could arise from differences or changes in reporting.

First, the results are unique to reports of elder financial exploitation that are more likely to be affected by the policy. Table 7 shows that the drop in elder financial exploitation involving fund transfers is robust to controlling for the county-month number of elder financial exploitation less likely to be affected by the policy. Column (2) shows that the drop in abuse involving fund

[9] 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.

transfers is robust to controlling for the number of abuse reports from money services businesses, which do not tend to hire investment advisers and brokers, the primary deputies. Relatedly, Internet Appendix Table A10 shows evidence of a decline in elder abuse reports from depository institutions (bank holding companies) and some evidence of a drop in abuse reports from standalone securities firms (broker-dealer firms) but no such decline in reports from money services businesses. Table 7 Column (3) shows a decline in abuse involving fund transfers after controlling for the county-month number of abuse cases involving credit cards (transactions and less likely to be under the purview of an adviser or broker), bank cashier checks and money orders (requires significant scrutiny already), home equity lines of credit (closing process requires a substantial application), mutual funds (policy does not protect transactions), and foreign currency (rules operate in the U.S.).

[Insert Table 7 Here]

Second, reporting to the FinCEN database (our source of data for elder abuse cases) is mandated for all transactions that involve more than $5,000, and failure to report could result in criminal penalties for financial institutions. This reporting requirement and the reporting threshold did not change with a state's adoption of the Model Act.

While there is no evidence of underreporting of abuse cases to the FinCEN database, it remains a possibility. Consequently, the frequency and magnitude of elder abuse could be even higher. Any underreporting is unlikely to be a problem for our analysis for a few reasons. First, if underreporting existed, the new rules would have raised awareness about elder abuse and likely decreased such underreporting. This resulting increase in reporting would works against our finding that the new laws decreased elder financial abuse. Second, for underreporting to be a confounding factor for our analysis, the underreporting pattern would have to be correlated with the staggered adoption of the *Model Act* across states or with whether a state adopts Model Act. 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.

Admittedly, Figure 2 shows that reports of elder financial exploitation have been increasing since 2014. However, Figure 3 shows that we largely remove such aggregate increase in reports from our analysis with time fixed effects. In Figure 3, we plot the state-level elder abuse case trends (up to year 2016, the earliest adoption year of Model Act across states) after removing the aggregate time trend, and there is no remaining pre-trend for any states.

In addition, we use regression analysis to show that 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 Internet Appendix Table A5, 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.

While there was no concomitant change in the reporting requirements of suspicious activity to FinCEN (our main source of data), some states adopting the Model Act started to mandate reporting to Adult Protective Services (APS) and sharing records with state regulators. Importantly, these changes in reporting requirements are independent of the reporting requirements to FinCEN. 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."

Lastly, there is no drop in suspicious activity reports unrelated to financial exploitation. Internet Appendix Table A9 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. And, the effect is not driven by one state; Internet Appendix Figure A4 shows that the static effect documented in Table 4 Column (1) is robust to dropping any state. And, we also show that the effects are robust to changing the sample starting year or end year in Table A6 and Table A7, respectively.

5.3.6. Collapsing at more aggregate levels to reduce sparsity

Because elder abuse at the county-month level is somewhat sparse, with 80% of county-month observations being zero, we collapse the dataset at the state-month level and repeat our DiD analysis. After collapsing the data, only 4% of state-months have zero reports. Despite removing a substantial amount of variation, Internet Appendix Table A4 shows that we also find a significant drop in the state-month number of reports across the same formulations of the outcome variable as in Table 4. In fact, Column (2) shows a significant drop in abuse cases after six months rather than one year.

5.3.7. Confounding regulatory changes

A related regulatory change aimed at protecting seniors is the *Senior Safe Act*. This 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 is a national rule change. Additionally, our results are primarily identified by comparing treated and never-treated counties (see Table 5), which were affected by the *Senior Safe Act* at the same time. In Internet Appendix Table A7, we find similar results when only including sample months prior to 2018. 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.

5.4. The Presence of Deputies, and the Types of Deputies

The rule change should be more effective in treated counties with a higher concentration of deputies, all else equal, if abuse falls because of their actions. We take advantage of our data from the SEC's IAPD and FINRA's BrokerCheck databases to characterize the heterogeneity in investment advisers and brokers across counties. We study this question using a triple DiD design, in which we interact $Post_{st}$ with measures of these county attributes. Importantly, we also control for the interaction of $Post_{st}$ with each existing control variable, 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 advisers in a county, we also interact $Post_{st}$ with the controls related to the number of elderly, the average level of educational attainment, and income. This approach addresses the concern that the per capita number of deputies is correlated with these other county attributes and we are just capturing a larger effect in wealthier counties, for example.

Table 8 presents the results. Consistent with abuse falling because of deputization, Table 8 Columns (1) and (2) show that the drop in elder abuse is greater in counties with more investment adviser representatives per capita and more brokers per capita. The interaction terms are both negative and highly significant. Note that the measures of advisers and brokers per capita are standardized prior to forming the interactions. A standard deviation increase in the presence of deputies predicts a 0.85 larger decline in abuse cases per month. While the coefficients may suggest that counties with low deputies see an increase in abuse, this interpretation is incorrect, as in an alternative specification with an indicator variable that equals one if the county has a high per capita presence of deputies, only the indicator loads negatively. Relatedly, in Internet Appendix Table A12, we show that there is no effect in counties with no deputies.

[Insert Table 8 Here]

The similarity in the coefficients in Table 8 Columns (1) and (2) is expected because there is a high correlation in the per capita number of advisers and brokers across counties. Nevertheless, it is interesting to examine whether the policy is more related to the presence of advisers than to the presence of brokers using a horse race. Column (3) shows that the relation with brokers per capita is not robust to controlling for the presence of advisers per capita. Relatedly, Column (4) shows that the effect is not related to the per capita presence of pure brokers (brokers who are not dual-registered as advisers). With the caveat that these two measures are highly correlated, this dichotomy in the effect between investment advisers and brokers is consistent with brokers having a more arms-length and transactional relationship with clients than investment advisers.[10] 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 an 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. 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.

Several pieces of additional evidence supports the possibility that brokers are less effective deputies for this policy. Internet Appendix Table A3 shows that the drop in elder abuse is not significantly weaker in states that adopt the Model Act after FINRA Rules 2165 and 4512. Given

[10]See https://www.investor.gov/home/welcome-investor-gov-crs and https://www.sec.gov/rules/interp/2019/ia-5248.pdf.

the similarity in between these FINRA rules and the NASAA Model Act, this finding may be due to the fact that the FINRA legislation is specific to brokers. Also, Internet Appendix Table A10 finds a strong drop in abuse reported by bank holding companies (Column 1) and a less significant drop in abuse reported by pure broker-dealers (Column 3). Broker-dealer firms tend to employ brokers only, and bank holding companies employ both advisers and brokers. We caveat, however, that Table 3 shows that only 1.5% of abuse reports come from pure broker-dealer firms so that this lack of a significant decline may simply be because there are not enough reports from such firms with which to evaluate the policy. It is important to highlight that broker-dealers exist within bank holding firms too, which make up the bulk of reports. But, since reports are separated out for pure broker-dealers, it may be informative to examine those separately.

An alternative interpretation for the dichotomy in the effect across investment advisers and brokers is that in communities with more advisers, there was more elder financial exploitation and therefore deputization had a larger impact. However, the opposite seems to be the case. Internet Appendix Table A11 Column (3) shows a positive relation between the presence of brokers and elder abuse rates prior to the rule change, while the proportion of investment advisers is negatively related to abuse rates.

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 9 column (1) shows 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. Alternatively, family members and caregivers perpetrating abuse against wealthier persons are more financially sophisticated. By contrast column (5) indicates no evidence that whether advisers charge hourly fees, commissions, or fixed fees for services matters for the effect.[11]

[Insert Table 9 Here]

5.5. Heterogeneous Effects by Existing Safeguards and Social Incentives

This section examines whether the effects of deputization vary with existing protections within social communities. 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

[11]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.

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.[12] 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, whereas more socially-connected elderly persons benefit less.

In Column (4), we further examine whether the effects vary with the county-level Social Capital Index. This index captures information on volunteering, public meeting attendance, non-profit organization participants per capita, and more. To the extent that social capital describes the set of values or norms shared by members in a community and fosters cooperation, these values, norms, and cooperation should offer protections to seniors ex ante. Our results are consistent with this hypothesis: In areas with a higher social capital index, the effects are weaker.

[Insert Table 10 Here]

Another type of safeguard may be a more ethical community. 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 (e.g. Guiso et al., 2003; Grullon et al., 2009). The weaker effect in areas with more religious congregations per capita could be consistent with that form of protection ex ante. However, column (5) suggests that the effect is more negative when the number of religious adherents per capita is higher.

5.6. 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 Internet Appendix Table A14 by gathering all of the disclosures individual advisers and brokers must make regarding regulatory actions and misconduct. In columns (1) and (2), we do not observe a statistically significant increase in disclosures of regulatory actions taken against advisers and brokers

[12] 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).

following adoption of the Model Act. If regulators became more active, we would have expected an increase in regulatory actions. Due to data limitations, we conduct these 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.

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 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 Section 5.4 suggests that the policy is more related to investment advisers than to brokers.

Lastly, deputies may act to manage their reputations. However, we find little support for this possible mechanism in the data. Because of strict privacy laws, 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 A15. Neither the SEC's IAPD website nor FINRA's BrokerCheck website discloses such information regarding brokers and advisers.

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 of the Model Act Across States

The map shows the staggered adoption of the Model Act across states through December 2020 as listed in Table 1.

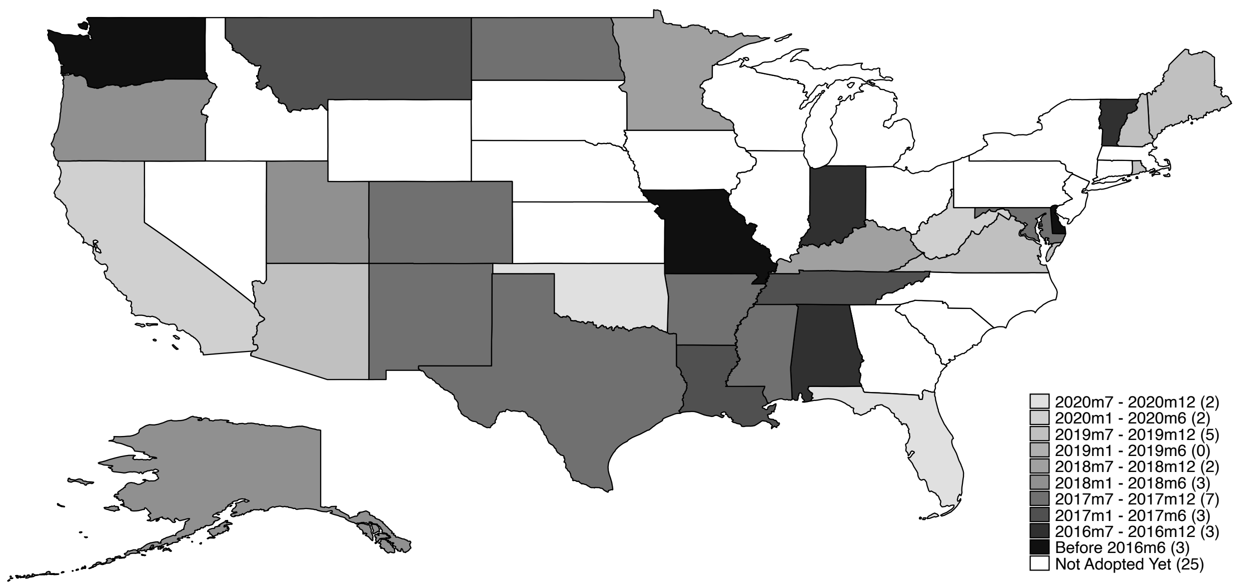


Figure 2. Elder Financial Exploitation by Month

This figure depicts, for each month, the natural logarithm of the total number of suspicious activity reports submitted to FinCEN that are flagged as related to elder financial exploitation in the United States. The category for suspicious activity reports involving elder financial exploitation was introduced at FinCEN in 2012. To remove the steep rise in reports due to the new category introduction, all of our empirical work starts at the red vertical line at January 2014. Thus our main sample period is January 2014 to December 2020. In Internet Appendix Table A6, we show that our results are robust to varying the sample start dates.

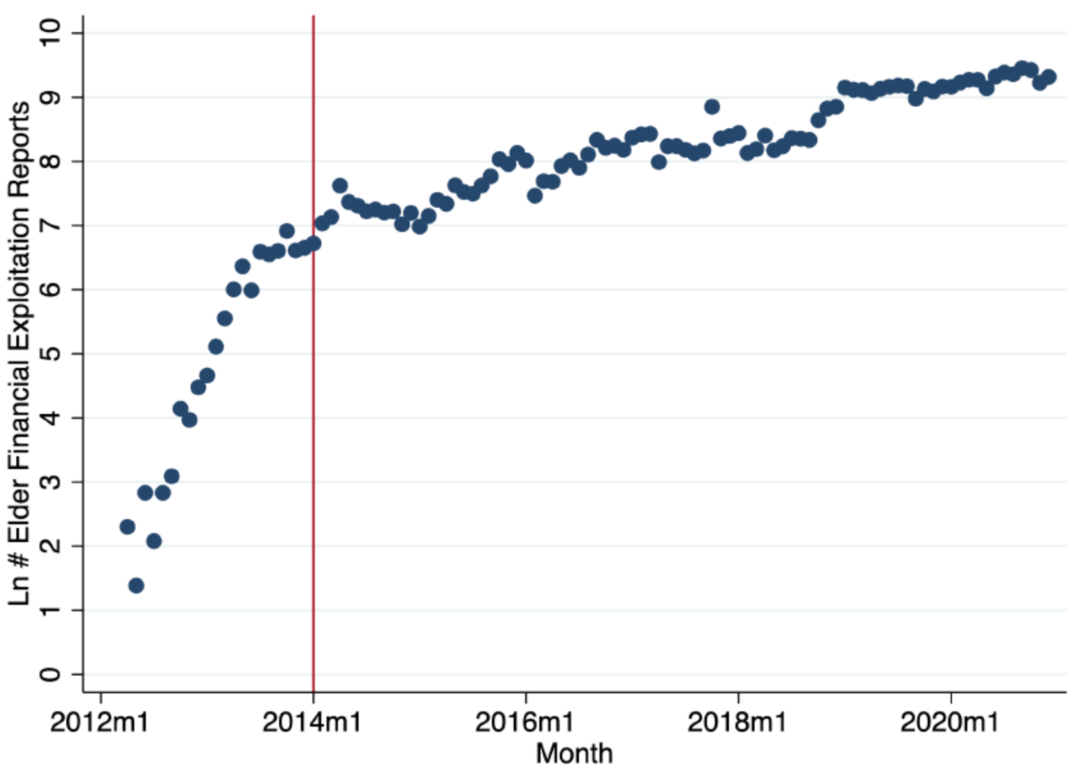


Figure 3. State Trends in Elder Financial Abuse Prior to Deputization

This figure shows the trends in the monthly, state-level number of elder financial exploitation reports. We first estimate the nationwide monthly trend in elder financial exploitation reports with year-month fixed effects and remove this trend. We also estimate and remove a state-specific linear trend estimated using pre-treatment data per Goodman-Bacon (2021). In our regression analyses, we likewise estimate and control for county-specific linear trends. Please see Internet Appendix Figure A1 for the same figure without removing the linear trend. The sample for this figure begins in January 2014 and ends in June 2016, which is just before the NASAA Model Act becomes effective for the earliest adopters.

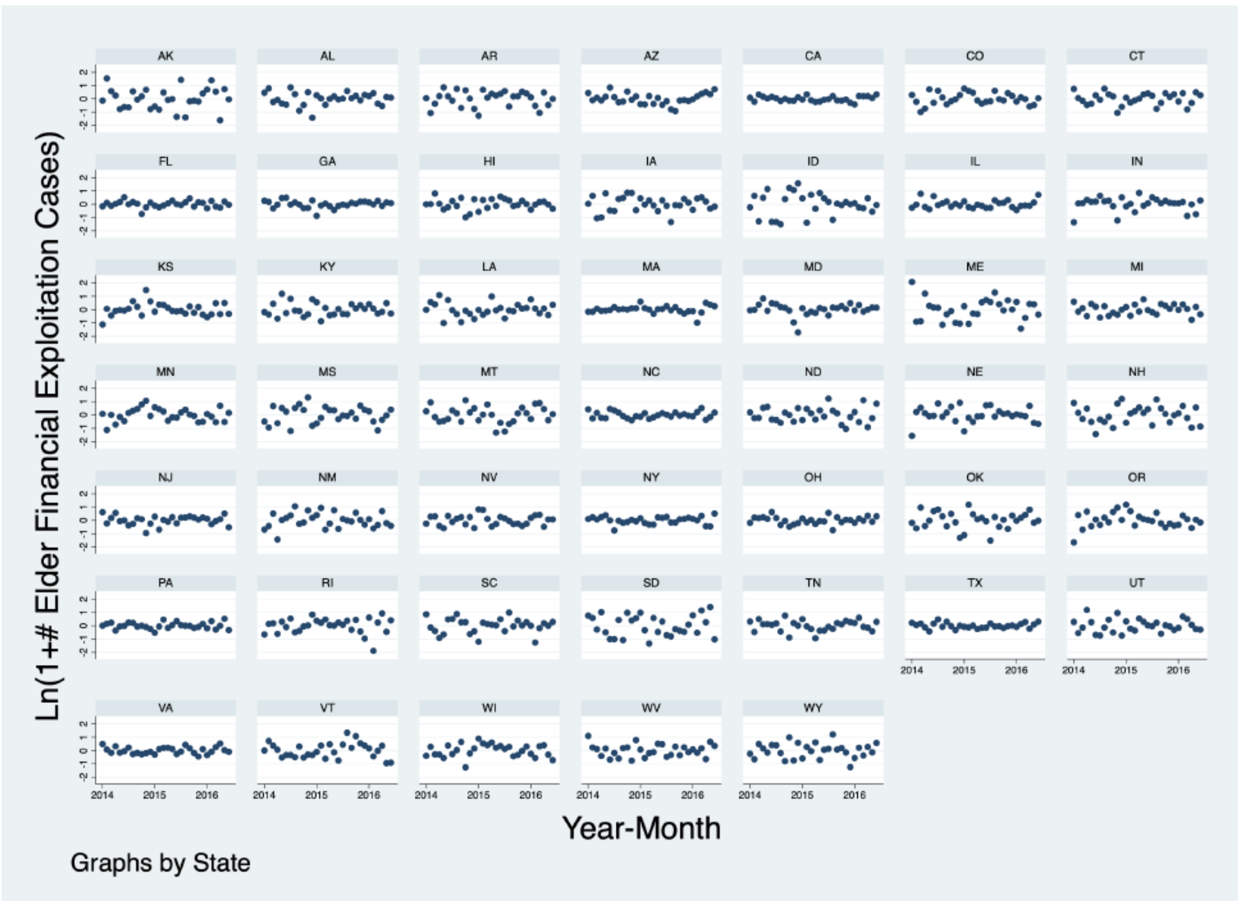
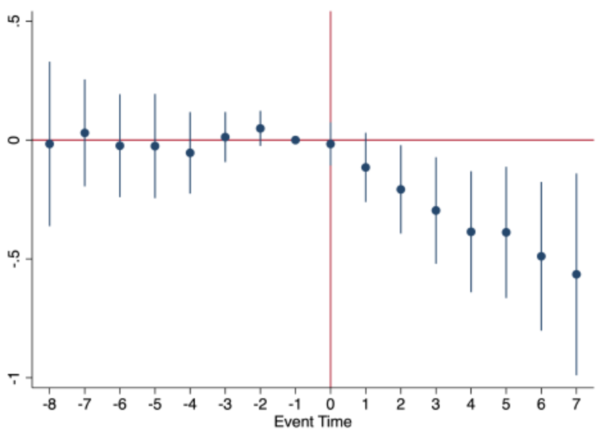


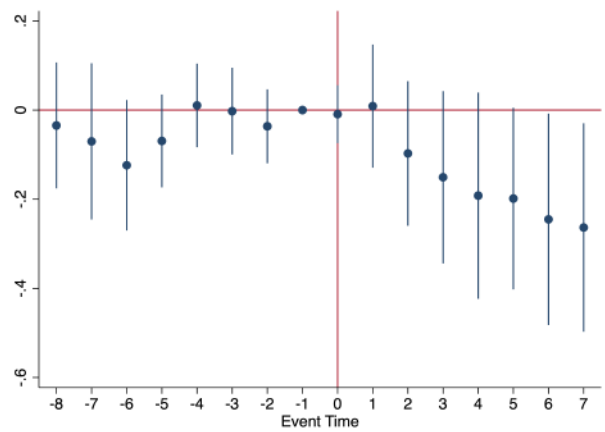
Figure 4. Effect of Deputization on Elder Financial Exploitation

The event-time figure shows the dynamic effect of deputizing financial professionals on elder financial exploitation around the month a state adopts the Model Act. We plot the coefficients on the event-time indicators from the dynamic DiD regression in Equation 3. Note that to simplify the figures and tables, we estimate the effect using monthly data for the six month intervals around the month of adoption. Thus, the effect estimated at $t = 0$ denotes the effect in months zero to five since adoption. The red vertical line at $t = 0$ indicates the beginning of treatment for a state. Figures (a), (c), and (d) are estimated using Ordinary Least Squares (OLS) regressions, while Figure (b) is estimated using a Poisson regression. Figures (e)-(i) repeat the event-time plots using only elder financial exploitation involving fund transfers. Note that if a state does not adopt the Model Act by 2020, then the event time indicators are all zero. Year-month and county fixed effects are included. The time-varying county controls in Table 3 are also included. We show 90% confidence intervals based on standard errors clustered by state. We omit the indicator for the six months before the month of treatment.

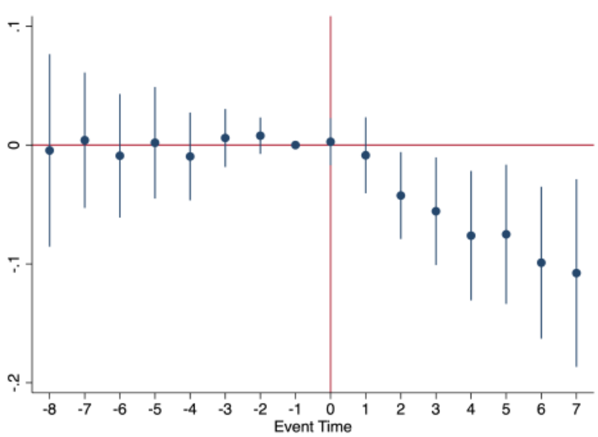
Y=Elder Financial Exploitation Cases



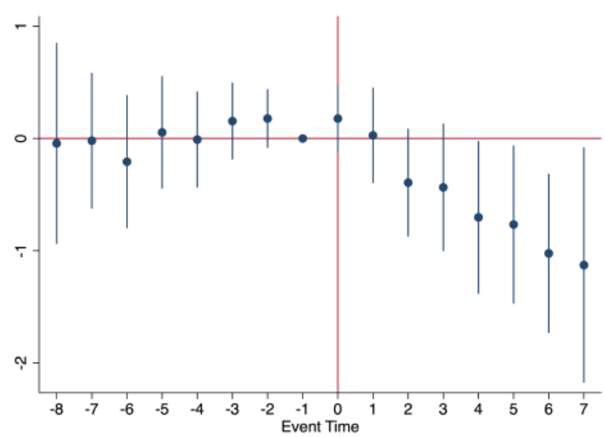
(a) Y (OLS)



(b) Y (Poisson)

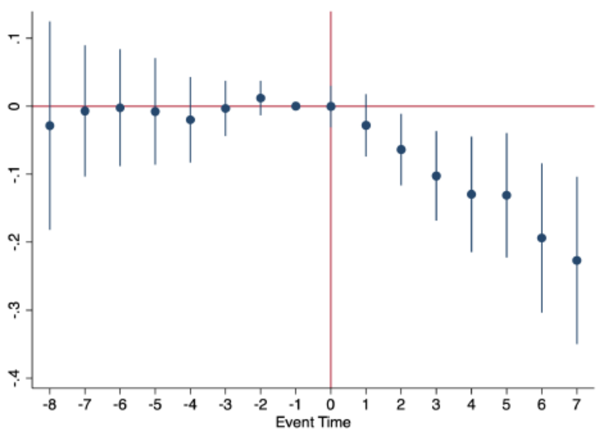


(c) Ln(1+Y)

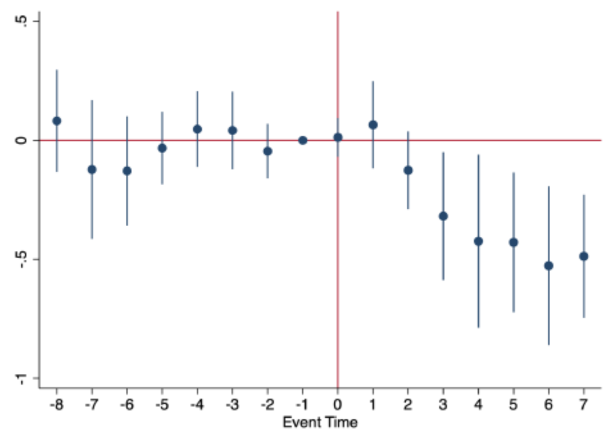


(d) Y/Pop. 65+×100,000

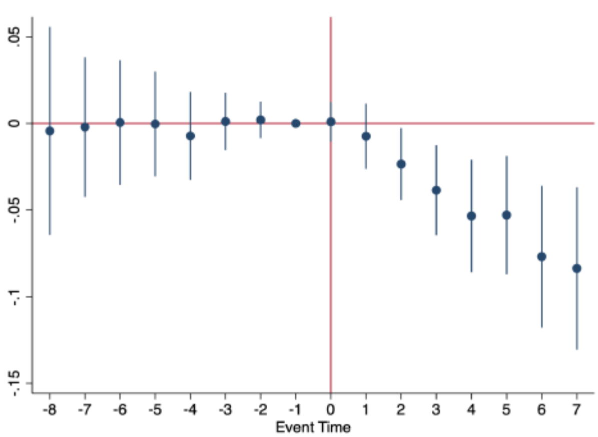
Z=Elder Financial Exploitation Cases *Involving Fund Transfers*



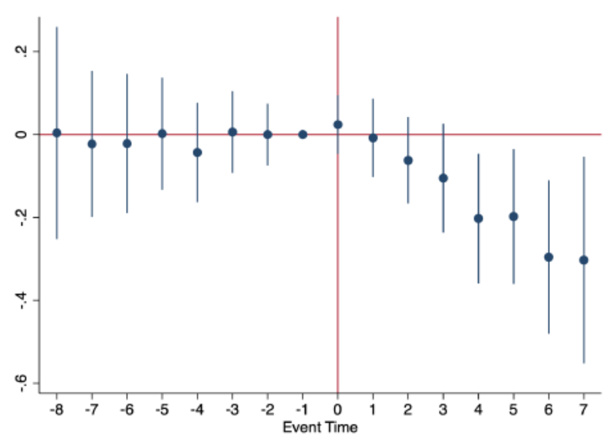
(f) Z (OLS)



(g) Z (Poisson)



(h) Ln(1+Z)



(i) Z/Pop. 65+×100,000

Figure 5. 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 30 states that adopted the Model Act by December 2020. The corresponding regression results are reported in panel A of Internet Appendix Table A2. The variable plotted on the y-axis, *Group of Adoption*, is equal to 1 for the earliest adopting state(s), 2 for the second earliest adopting state(s), 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 financial exploitation cases per 1,000 people in a state that are age 65 and above. *Frac Pop Above 65* measures the fraction of the population in a state that is age 65 and above. *Average Household Income* measures the average household income in a state. *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.

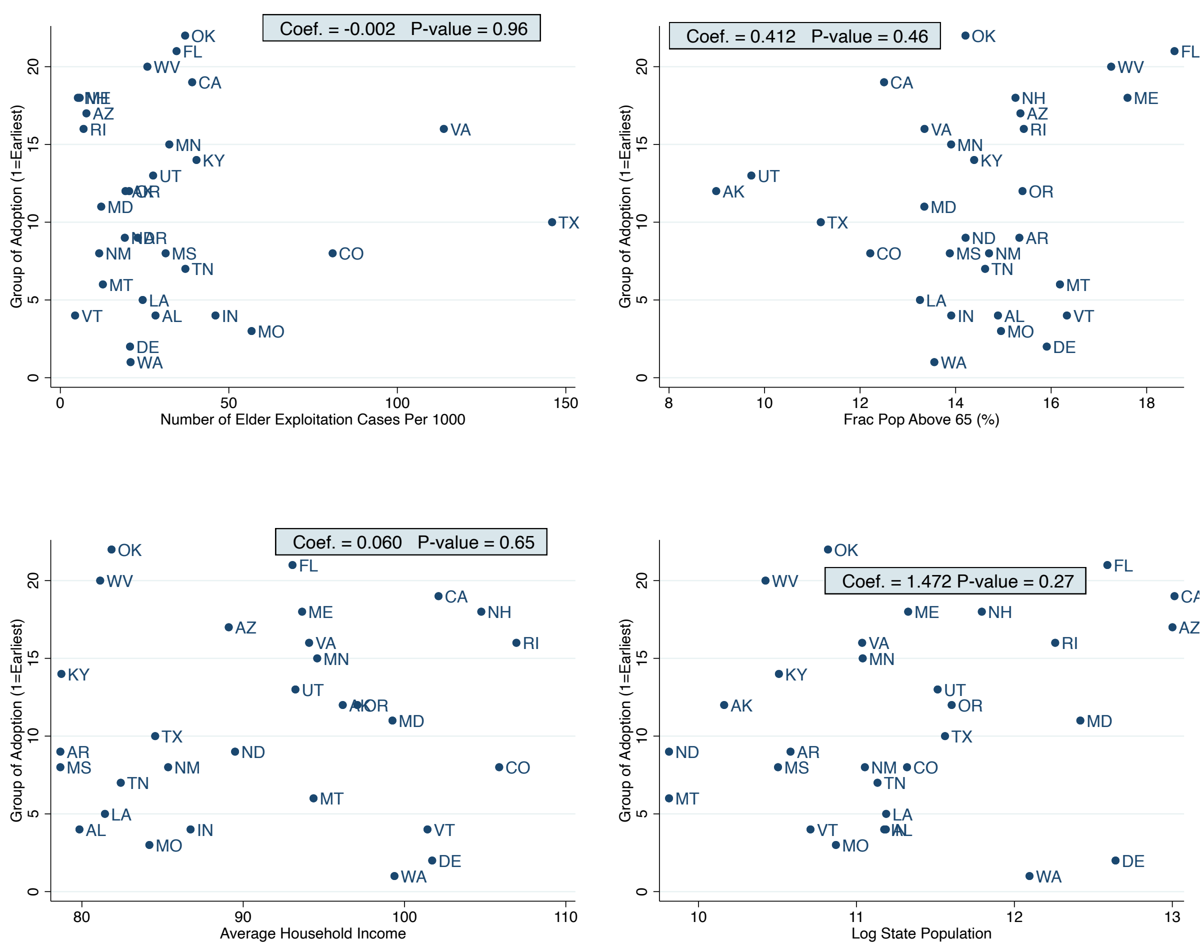
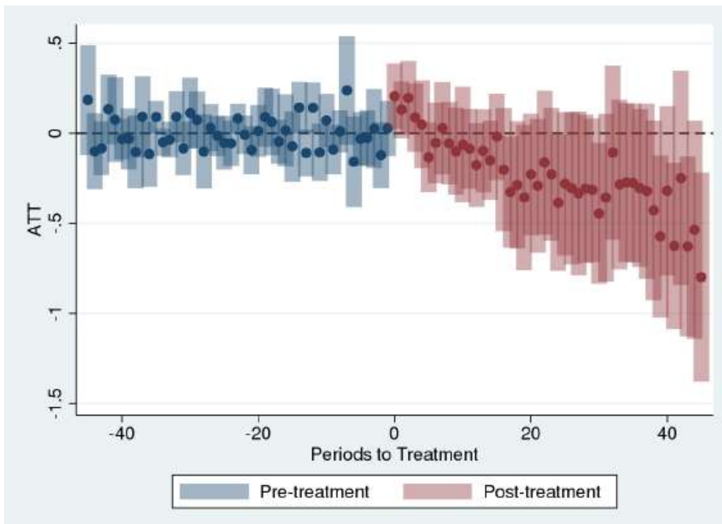
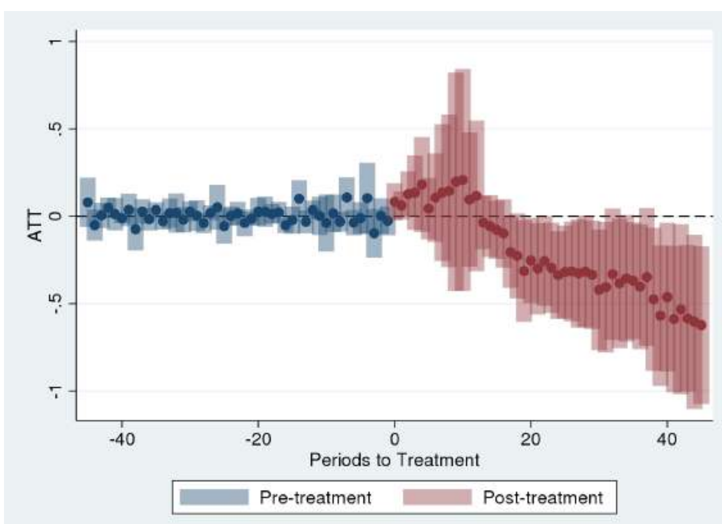


Figure 6. Estimating the Effect of Deputization using Only Never-Treated States as Controls

This figure estimates the monthly effect of deputizing financial professionals on elder financial exploitation around the date a state adopts the Model Act, using only never-treated states as controls per Callaway and Sant'Anna (2021). Specifically, the method estimates the DiD coefficient separately for all possible pairs of treated and never-treated states. The outcome variable in (a) is the number of elder financial exploitation cases in a county-month; the outcome in (b) is the number of abuse cases involving funds transfers. The lighter bands are 95% confidence intervals, and the darker bands are 90% confidence intervals, based on standard errors clustered by state.



(a) # Abuse Cases



(b) # Abuse Cases Involving Funds Transfers

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 through 2020. 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. If there is more than one effective date for a state, we use the earlier date.

State	**Passage Date**	**Effective Date**	**Applies to Whom**
AL	4/15/16	7/1/16	Broker-dealers and investment advisers
AK	4/17/17	1/1/18	Broker-dealers and investment advisers
AZ	5/13/19	8/27/19	Broker-dealers and investment advisers
AR	3/27/17	8/7/17	Broker-dealers and investment advisers
CA	9/6/19	1/1/20	Broker-dealers and investment advisers
CO	6/2/17	7/1/17	Broker-dealers and investment advisers
DE	9/30/14	9/30/14	Financial Institutions*
DE	8/29/18	11/27/18	Broker-dealers and investment advisers
FL	6/30/20	7/1/20	Broker-dealers and investment advisers
IN	3/21/16	7/1/16	Broker-dealers
IN	4/24/17	7/1/17	Investment advisers
KY	4/10/18	7/14/18	Financial Institutions*
LA	6/17/16	1/1/17	Broker-dealers and investment advisers
ME	4/2/19	9/19/19	Broker-dealers and investment advisers
MD	5/27/17	10/1/17	Broker-dealers and investment advisers
MN	5/19/18	8/1/18	Broker-dealers and investment advisers
MO	6/12/15	8/28/15	Broker-dealers
MS	3/27/17	7/1/17	Broker-dealers and investment advisers
MT	3/22/17	3/22/17	Broker-dealers and investment advisers
NH	7/10/19	9/8/19	Broker-dealers and investment advisers
NM	4/6/17	7/1/17	Broker-dealers and investment advisers
ND	4/10/17	8/1/17	Broker-dealers and investment advisers
OK		11/1/20	Broker-dealers and investment advisers
OR	6/29/17	1/1/18	Broker-dealers and investment advisers
RI	7/15/19	7/15/19	Broker-dealers
TN	5/18/17	5/18/17	Broker-dealers and investment advisers
TX	6/1/17	9/1/17	Financial Institutions*
UT	3/16/18	5/8/18	Broker-dealers and investment advisers
VT		7/1/16	Broker-dealers and investment advisers
VA	3/18/19	7/1/19	Financial Institutions*
WV	3/7/20	6/5/20	Broker-dealers and investment advisers
WA	3/19/10	6/10/10	Financial Institutions*

TABLE 3. Summary Statistics

The sample period is January 2014 to December 2020. 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 financial exploitation of elderly persons reported to the Department of Treasury. *Elder Financial Exploitation Cases Per 100,000 Adults 65+* is the rate 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 hundred if there is at least one report of elder financial exploitation in a county-month. *Advisers Per 1,000* (*Brokers Per 1,000*) is the number of investment advisers (brokers) in a county divided by the total number of persons that are 16 years of age or older, multiplied by 1,000. *Population Above 65* is the number of persons 65 years of age or older. *Fraction of Population Above 65* is the proportion of a county's population that is 65 years of age or older. *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. *Subprime (65+)* is the percentage of elderly residents with a credit score below 660, based on credit records. *Low Income (65+)* is the percentage of elderly residents with incomes below the national median, based on credit records. *Average Age (65+)* is the average age of elderly residents in a county. *Male (65+)* is the percentage of elderly residents that are male. *Married (65+)* is the percentage 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. *Bachelor or Higher* is the percentage of county adults with at least a bachelor degree. *Religious Adherents Per 1000* is the number of individuals with and without an affiliation to a congregation per 1,000 individuals. *Religious Congregation per 1000* is the number of religious congregations per 1,000 individuals. Panel B reports characteristics of the abuse reports submitted to the U.S. Treasury's FinCEN database. Specifically, for the sample of county-months with at least one abuse case, the table shows the average county-month fraction of reports of elder financial exploitation classified by the instrument involved and the industry of the reporting institution.

Panel A: County-Month Summary Statistics

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Mean	SD	p10	p50	p90	N
Elder Financial Exploitation Cases	1.3	4.1	0.0	0.0	3.0	263,676
Elder Financial Exploitation Cases Per 100,000 Adults 65+	6.4	31.7	0.0	0.0	16.9	263,676
Elder Financial Exploitation Probability (%)	20.3	40.2	0.0	0.0	100.0	263,676
Adviser Per 1,000	0.5	1.0	0.0	0.2	1.1	263,676
Brokers Per 1,000	0.8	2.0	0.0	0.5	1.8	263,676
Population Above 65	15,133.3	43,330.6	972.4	4,513.3	31,137.9	263,676
% Fraction of Population Above 65	17.9	4.6	12.4	17.6	23.7	263,676
Vantage Score (65+)	724.6	53.9	696.2	730.1	755.5	263,676
% Subprime (65+)	19.0	10.4	7.5	17.5	33.3	263,676
% Low Income (65+)	52.0	12.6	37.5	51.8	66.7	263,676
Average Age (65+)	76.8	5.2	74.9	77.2	79.3	263,676
% Male (65+)	47.6	9.6	38.5	47.3	57.9	263,676
% Married (65+)	54.3	11.6	42.0	54.1	66.7	263,676
Household Income (65+)	90.1	16.3	72.6	88.7	110.2	263,676
% Household Debt-to-Income Ratio (65+)	6.5	2.3	3.6	6.5	9.2	263,676
Average Retirement Income	21,992.3	5,321.3	16,294.0	21,056.0	28,987.0	263,676
% Bachelor or Higher	21.2	9.3	12.0	18.9	33.5	263,676
Religious Adherent Per 1000	514.1	181.7	295.4	497.2	753.5	263,676
Religious Congregation Per 1000	2.4	1.4	0.9	2.2	4.2	263,676

Panel B: The Composition of FinCEN Elder Financial Exploitation Cases by County-Month

Instrument Involved		Product Involved	
U.S. Currency	42.2%	Debit Card	34.7%
Funds Transfer	23.9%	Deposit Account	30.0%
Personal/Business Check	20.0%	Credit Card	9.5%
Bank/Cashier's Check	6.5%	Other	25.8%
Other	7.4%		
Regulator of Reporting Firm		**Industry of Reporting Firm**	
OCC	33.7%	Depository Institution	71.8%
IRS	26.6%	Money Services Business	26.2%
FRB	19.6%	Securities/Futures	1.5%
FDIC	13.8%	Other	0.5%
Other	6.3%		

TABLE 4. Effects of Deputization on Elder Financial Exploitation

This table presents DiD estimates of the effect of deputizing financial professionals on elder financial exploitation. The outcome in columns (1) to (3) is the number of elder financial exploitation cases in a county-month. Column (3) estimates a Poisson model. The outcome in column (4) is the natural logarithm of one plus the number of elder financial exploitation cases in a county-month. The outcome in column (5) is the number of cases per 100,000 persons 65 years of age or older. A similar setup exists in columns (6) to (10), but the outcome is only based on the number of abuse cases involving fund transfers. *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 coefficients on *Pre #* and *Post #* estimate the dynamic effect of deputization over the six-months periods before and after the month financial professionals are deputized. For example, *Post 0* is the effect of deputization in months $t = 0$ to $t = 5$, with $t = 0$ being the month of deputization. We omit *Pre 1*, the six months prior to deputization. The control variables, defined in Table 3, include *Vantage Score (65+)*, *% Subprime (65+)*, *% Low Income (65+)*, *Average Age (65+)*, *% Male (65+)*, *% Married (65+)*, *Household Income (65+)*, *% Household Debt-to-Income Ratio (65+)*, *Population Above 65*, and *Bachelor or Higher*. Specifications include county and year-month fixed effects as well as a county-linear trend in elder financial abuse cases, estimated using data prior to July 2016 (Goodman-Bacon, 2021). The sample size drops in columns (3) and (8) because a Poisson regression with county fixed effects removes counties without any variation in elder financial exploitation. Standard errors clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Y = Elder Financial Exploitation Cases					Z = Elder Exploitation Involving Fund Transfers				
	Y			Ln(1+Y)	Y/Pop. 65+	Z			Ln(1+Z)	Z/Pop. 65+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Post	-0.186**					-0.050*				
	(0.092)					(0.026)				
Pre 8		-0.016	-0.034	0.008	-0.044		-0.029	0.082	-0.005	0.003
		(0.206)	(0.086)	(0.034)	(0.534)		(0.096)	(0.130)	(0.037)	(0.156)
Pre 7		0.030	-0.070	0.011	-0.020		-0.006	-0.123	-0.002	-0.021
		(0.134)	(0.107)	(0.025)	(0.360)		(0.060)	(0.177)	(0.025)	(0.107)
Pre 6		-0.024	-0.124	-0.005	-0.207		-0.000	-0.129	0.001	-0.020
		(0.129)	(0.089)	(0.024)	(0.354)		(0.053)	(0.140)	(0.022)	(0.102)
Pre 5		-0.025	-0.069	0.002	0.054		-0.005	-0.033	0.001	0.005
		(0.131)	(0.063)	(0.021)	(0.299)		(0.048)	(0.093)	(0.019)	(0.082)
Pre 4		-0.054	0.011	-0.009	-0.010		-0.017	0.047	-0.006	-0.040
		(0.102)	(0.057)	(0.017)	(0.256)		(0.039)	(0.097)	(0.016)	(0.073)
Pre 3		0.013	-0.002	0.007	0.154		-0.000	0.042	0.002	0.009
		(0.063)	(0.059)	(0.013)	(0.204)		(0.025)	(0.099)	(0.010)	(0.059)
Pre 2		0.049	-0.036	0.009	0.178		0.014	-0.046	0.003	0.002
		(0.044)	(0.050)	(0.009)	(0.156)		(0.015)	(0.070)	(0.006)	(0.045)
Pre 1		.	.	.	.		.	.	.	.
Post 0		-0.016	-0.009	0.002	0.177		0.001	0.012	0.001	0.025
		(0.054)	(0.039)	(0.011)	(0.179)		(0.018)	(0.050)	(0.007)	(0.042)
Post 1		-0.115	0.009	-0.005	0.028		-0.027	0.065	-0.007	-0.007
		(0.087)	(0.084)	(0.017)	(0.254)		(0.028)	(0.111)	(0.011)	(0.057)
Post 2		-0.208*	-0.097	-0.034*	-0.393		-0.062*	-0.126	-0.023*	-0.061
		(0.111)	(0.099)	(0.018)	(0.287)		(0.032)	(0.099)	(0.013)	(0.063)
Post 3		-0.296**	-0.151	-0.046*	-0.436		-0.100**	-0.319*	-0.038**	-0.102
		(0.134)	(0.117)	(0.023)	(0.339)		(0.040)	(0.163)	(0.016)	(0.079)
Post 4		-0.386**	-0.192	-0.065**	-0.702*		-0.125**	-0.424*	-0.052**	-0.198**
		(0.152)	(0.141)	(0.028)	(0.406)		(0.052)	(0.221)	(0.020)	(0.094)
Post 5		-0.388**	-0.198	-0.068**	-0.766*		-0.124**	-0.429**	-0.050**	-0.190*
		(0.165)	(0.124)	(0.029)	(0.420)		(0.056)	(0.179)	(0.021)	(0.098)
Post 6		-0.489**	-0.245*	-0.088**	-1.023**		-0.184***	-0.527***	-0.074***	-0.286**
		(0.187)	(0.144)	(0.034)	(0.423)		(0.067)	(0.203)	(0.025)	(0.111)
Post 7		-0.565**	-0.263*	-0.100*	-1.128*		-0.207***	-0.488***	-0.077***	-0.283*
		(0.253)	(0.142)	(0.053)	(0.625)		(0.073)	(0.158)	(0.028)	(0.148)
Specification	OLS	OLS	Poisson	OLS	OLS	OLS	OLS	Poisson	OLS	OLS
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Linear Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.67	0.67	.	0.62	0.22	0.63	0.59	.	0.58	0.23
# Counties	3139	3139	2677	3139	3139	3139	3139	2342	3139	3139
Observations	245169	245169	210072	245169	245169	245169	245169	183755	245169	245169

TABLE 5. Goodman-Bacon Decomposition

This table shows the Goodman-Bacon (2021) decomposition of our staggered difference-in-difference regression coefficient estimate in Table 4 column (1) of -0.186. The preferred source of variation in the presence of a gradual treatment response is *Treated vs Never Treated*, which estimates the effect using only the non-treated states as controls. The most problematic source of variation in the presence of a gradual treatment responses is *Later Treated vs Earlier Control*, which estimates the effect using the states treated earlier as controls for the states treated later. *Earlier Treated vs Later Control* estimates the effect using the states treated later as controls for the states treated earlier. *Treated vs Already Treated* estimates the effect using states that are always treated during the sample period as controls for states treated during the sample period.

Variation	**Beta**	**Weight**
Treated vs Never Treated	-0.246	0.744
Earlier Treated vs Later Control	-0.024	0.164
Later Treated vs Earlier Control	0.049	0.091
Treated vs Already Treated	-0.055	0.001

TABLE 6. Effects of Deputization on Elder Exploitation: Matched Sample Analyses

This table shows the difference-in-difference analysis in Table 4 using a sample of matched counties. We implement the following minimum distance matching procedure: for each county, we calculate its geometric distance to all other counties based on a vector of covariates. The covariates are the controls in Table 4, which Table 3 defines, and include *Vantage Score (65+)*, *% Subprime (65+)*, *% Low Income (65+)*, *Average Age (65+)*, *% Male (65+)*, *% Married (65+)*, *Household Income (65+)*, *% Household Debt-to-Income Ratio (65+)*, *Population Above 65*, and *% Bachelor or Higher*. Geometric distance is calculated as the square root of the sum of the squares of the differences in covariates between two counties. Mathematically, it is expressed as $d_{ij} = \sqrt{(x_{1i} - x_{1j})^2 + (x_{2i} - x_{2j})^2 + ... + (x_{Ni} - x_{Nj})^2}$, where x_1, x_2, ..., x_N are standardized covariates, and i and j denote counties. All covariates are standardized to have a mean of zero and a standard deviation of one to receive equal weights. Next, for each county, we select a pair county that has the smallest geometric distance to the county, locates in a different state, and receives the treatment at a different point in time. Then, to ensure we use only high-quality matches, we keep the county pairs that have a geometric distance below the 25^{th} percentile of the distance distribution. Last, we use the subsamples of matched county pairs to perform difference-in-difference regressions, while including a set of matched-pair fixed effects. The outcome in column (1) is the number of elder financial exploitation cases in a county-month. The outcome in column (2) is the number of cases involving fund transfers. The coefficients on *Pre #* and *Post #* estimate the dynamic effect of deputization over the six-months periods before and after the month a state deputizes financial professionals by adoption the Model Act provisions. For example, *Post 0* is the effect of deputization in months $t = 0$ to $t = 5$, with $t = 0$ being the month of deputization. We omit *Pre 1*, the six months prior to deputization. Standard errors clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. We also present the covariate balance test on the matched sample of counties in Panel B, where *Treat* is an indicator variable that equals to one if a county is in the State deputizing professionals first within a pair.

	Elder Financial Exploitation Cases	Elder Exploitation Involving Fund Transfer Cases
	(1)	(2)
	25^{th} Percentile	25^{th} Percentile
Pre 8	-0.058	0.004
	(0.422)	(0.168)
Pre 7	-0.017	-0.006
	(0.318)	(0.127)
Pre 6	-0.187	-0.019
	(0.304)	(0.104)
Pre 5	-0.073	-0.055
	(0.304)	(0.101)
Pre 4	0.012	-0.046
	(0.179)	(0.073)
Pre 3	0.057	0.003
	(0.111)	(0.048)
Pre 2	0.075	0.043
	(0.124)	(0.057)
Pre 1	.	.
Post 0	0.039	0.020
	(0.131)	(0.042)
Post 1	-0.287	-0.082
	(0.180)	(0.057)
Post 2	-0.405*	-0.147*
	(0.213)	(0.076)
Post 3	-0.167	-0.119
	(0.260)	(0.090)
Post 4	-0.562*	-0.241*
	(0.296)	(0.123)
Post 5	-0.487*	-0.228**
	(0.289)	(0.108)
Post 6	-0.677**	-0.301*
	(0.336)	(0.154)
Post 7	-0.667	-0.322*
	(0.441)	(0.167)
Pair FE	Yes	Yes
Year-Month FE	Yes	Yes
County FE	Yes	Yes
Adjusted R^2	0.66	0.67
# Counties	698	698
Observations	78689	78689

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

	Treat = 0		Treat = 1			
	Mean	SD	Mean	SD	P-value	Std. Diff.
Vantage Score (65+)	0.04	(0.58)	0.05	(0.61)	(0.75)	0.01
Fraction of Subprime (65+)	-0.04	(0.53)	-0.05	(0.57)	(0.61)	-0.02
Fraction of Low Income (65+)	-0.15	(0.60)	-0.14	(0.60)	(0.84)	0.01
Average Age (65+)	0.05	(0.53)	0.06	(0.55)	(0.77)	0.01
Fraction of Male (65+)	-0.07	(0.36)	-0.08	(0.37)	(0.81)	-0.01
Fraction of Married (65+)	-0.12	(0.49)	-0.11	(0.56)	(0.87)	0.01
Household Income (65+)	0.10	(0.71)	0.10	(0.73)	(0.85)	-0.01
Household Debt-to-Income Ratio (65+)	0.19	(0.52)	0.18	(0.55)	(0.58)	-0.02
Pop 65+	0.82	(0.85)	0.81	(0.85)	(0.87)	-0.01
Bachelor or Higher	0.30	(0.99)	0.29	(1.00)	(0.89)	-0.01
Observations	507		543			

TABLE 7. Effects of Deputization Robust to Controlling for Less-Affected Types of Elder Financial Exploitation

This table presents DiD estimates of the effect of deputizing financial professionals on elder financial exploitation (EFE) reports involving fund transfers, controlling for other types of EFE. Column (1) repeats Column (6) from Table 4. Column (2) controls for the county-month number of EFE reports from money services businesses, which do not employ the financial professionals deputized. Column (3) controls for other types of EFE that are less likely to be affected by the policy. Specifically, we control for reports involving credit cards, bank cashier checks, money orders, home equity lines of credit, mutual funds, foreign currency, insurance, and prepaid access. *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 control variables, defined in Table 3, include *Vantage Score (65+)*, *% Subprime (65+)*, *% Low Income (65+)*, *Average Age (65+)*, *% Male (65+)*, *% Married (65+)*, *Household Income (65+)*, *% Household Debt-to-Income Ratio (65+)*, *Population Above 65*, and *Bachelor or Higher*. Specifications include county and year-month fixed effects as well as a county-linear trend in elder financial abuse cases, estimated using data prior to July 2016 (Goodman-Bacon, 2021). Standard errors clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	# Elder Exploitation Reports Involving Fund Transfers		
	(1)	(2)	(3)
Post	-0.050*	-0.056**	-0.049**
	(0.026)	(0.026)	(0.021)
Reports - Money Services Business		0.150***	0.151***
		(0.037)	(0.043)
Reports - Credit Card Abuse			0.033
			(0.025)
Reports - Bank Cashier Check Abuse			0.295***
			(0.064)
Reports - HELOC Abuse			0.322***
			(0.050)
Reports - Mutual Fund			0.170*
			(0.095)
Reports - Money Orders			0.181***
			(0.050)
Reports - Foreign Currency			-0.016
			(0.156)
Reports - Insurance			0.336***
			(0.035)
Reports - Prepaid Access			0.011
			(0.044)
Year-Month FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
County-Linear Trend	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Adjusted R^2	0.63	0.66	0.70
# Counties	3139	3139	3139
Observations	245169	245169	245169

TABLE 8. Effects of Deputization and the Presence of Deputies

 # Elder Financial Exploitation Cases is 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 (Brokers)* is a county's per capita number of investment advisers (brokers). *Pure Brokers per Capita* is a county's per capita number of brokers that are not dual registered as investment advisers. 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 the year-month fixed effects to allow for different aggregate trends in areas with few and many deputies. Standard errors clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	# Elder Financial Exploitation Cases			
	(1)	(2)	(3)	(4)
Post	-0.130	-0.114	-0.139	-0.132
	(0.089)	(0.094)	(0.090)	(0.090)
Post × Investment Advisers per Capita	-0.888***		-0.578**	-0.750***
	(0.140)		(0.242)	(0.155)
Post × Brokers per Capita		-0.841***	-0.337	
		(0.150)	(0.251)	
Post × Pure Brokers per Capita				-0.183
				(0.153)
Year-Month FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
County-Linear Trend	Yes	Yes	Yes	Yes
Interacted Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.69	0.68	0.69	0.69
# Counties	3139	3139	3139	3139
Observations	245169	245169	245169	245169

TABLE 9. 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. *# Elder Financial Exploitation Cases* is 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. *Investment Advisers per Capita* 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. *Hourly* is the proportion of advisers associated with firms that charge an hourly fee for services. *Commissions* is the proportion of advisers associated with firms that charge commissions. *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 the year-month fixed effects to allow for different aggregate trends in areas with few and many deputies or with low and high AUM-per-Client. Standard errors clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	# Elder Financial Exploitation Cases				
	(1)	(2)	(3)	(4)	(5)
Post	-0.842***	-0.689***	-0.379***	-0.372***	-0.493***
	(0.220)	(0.234)	(0.122)	(0.121)	(0.109)
Post × Investment Advisers per Capita	-1.274	-2.115**	-0.770***	-0.749***	-0.319*
	(0.958)	(1.008)	(0.189)	(0.192)	(0.188)
Post × AUM-per-Client	-1.452***				-0.901***
	(0.387)				(0.139)
Post × Hourly		0.161			0.049
		(0.144)			(0.093)
Post × Commission			-0.123**		0.002
			(0.050)		(0.079)
Post × Fixed Fees				-0.149**	-0.125
				(0.072)	(0.127)
Year-Month FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
County-Linear Trend	Yes	Yes	Yes	Yes	Yes
Interacted Controls	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.56	0.55	0.63	0.63	0.64
# Counties	2198	2198	2198	2198	2198
Observations	178331	178720	178720	178720	178331

TABLE 10. Social Incentives

This table studies whether deputization is less effective in counties with more social connectedness and religiosity. *# Elder Financial Exploitation Cases* is 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. *Investment Advisers per Capita* 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. *Social Capital Index* is a measure of a county's social capital developed by the Social Capital Project from the U.S. Joint Economic Committee. 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 the year-month fixed effects to allow for different aggregate trends in areas with few and many deputies or with low and high AUM-per-Client. Standard errors clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	# Elder Financial Exploitation Cases				
	(1)	(2)	(3)	(4)	(5)
Post	-0.106	-0.092	-0.074	-0.206**	-0.198**
	(0.106)	(0.102)	(0.113)	(0.091)	(0.090)
Post × Investment Advisers per Capita	-0.890***	-0.791***	-0.982***	-0.995***	-0.796***
	(0.152)	(0.156)	(0.172)	(0.159)	(0.139)
Post × Social Connectedness Index	1.031***				
	(0.185)				
Post × Congregations Per 1000		0.975***			1.303***
		(0.153)			(0.186)
Post × Adherents Per 1000			0.223**		-0.297**
			(0.087)		(0.129)
Post × Social Capital Index				0.512***	0.391***
				(0.117)	(0.115)
Year-Month FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
County-Linear Trend	Yes	Yes	Yes	Yes	Yes
Interacted Controls	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.67	0.67	0.67	0.68	0.68
# Counties	3135	3139	3139	2990	2987
Observations	244887	245169	245169	232985	232787

Internet Appendix to
Deputizing Financial Institutions to Fight Elder Abuse

This Internet Appendix contains supplementary analyses. These include the following:

Figures

1. Figure A1 shows Figure 3 without removing the state-specific linear trends.
2. Figure A2 is a monthly event time plot.
3. Figure A3 further decomposes the Goodman-Bacon (2021) decomposition in Table 5.
4. Figure A4 shows the main effect dropping each state.

Tables

1. Table A1 provides a correlation table.
2. Table A2 examines the relation between state characteristics and the timing of adoption of the Model Act and whether a state adopts the Model Act.
3. Table A3 examines whether the effect varies before and after the national adoption of FINRA's Rules 2165 and 4512.
4. Table A4 shows the effect at the state-month level.
5. Table A5 Growth in Reporting from 2012 to 2016 and Timing of Model Act Adoption.
6. Table A6 shows main effect starting the sample in different years.
7. Table A7 shows main effect ending the sample in different years.
8. Table A8 shows the dynamics of the results in Table 8.
9. Table A9 shows no effect using placebo outcomes.
10. Table A10 shows no effect for money services business, which do not employ advisers and brokers.
11. Table A11 shows how a elder financial exploitation varies with a county's per-capita number of investment advisers and brokers.
12. Table A12 shows the main effect in counties with no deputies.
13. Table A13 shows the dynamics for elder financial exploitation involving various activities (e.g., fund transfers, credit cards, etc.).
14. Table A14 examines whether regulatory actions changed witht he policy.
15. Table A15 provides details for the Factiva news searches.

Appendix A. Robustness

Figure A1. Removing Aggregate Trend in Elder Financial Abuse
This figure complements Figure 3. It shows the trends in the state-level number of elder financial exploitation reports *only* removing the aggregate monthly trend in elder financial exploitation reports using year-month fixed effects. The sample for this figure begins in January 2014 and ends in June 2016, which is before the NASAA Model Act is recommended for adoption.

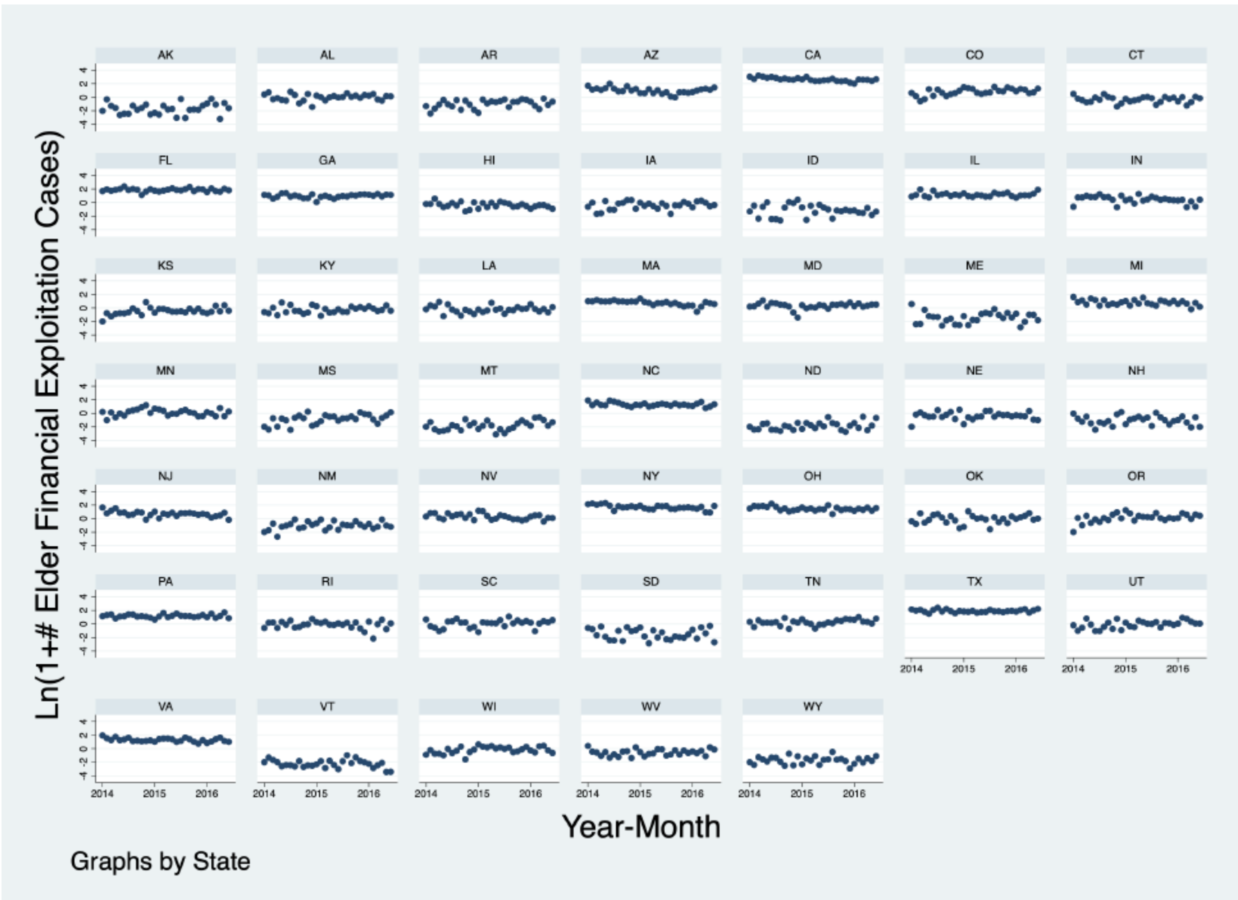


Figure A2. Dynamic DiD Estimates

This figure estimates the effect of deputizing financial professionals on elder financial exploitation around the date a state adopts the Model Act. The red vertical line at month zero indicates the month of treatment. The outcome variable is *# Elder Financial Exploitation Cases*, the natural logarithm of one plus the number of elder financial exploitation cases in a county-month. 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. Year-month and county fixed effects are included. 90% confidence intervals based on standard errors clustered by state. We omit the month six months before the month of treatment.

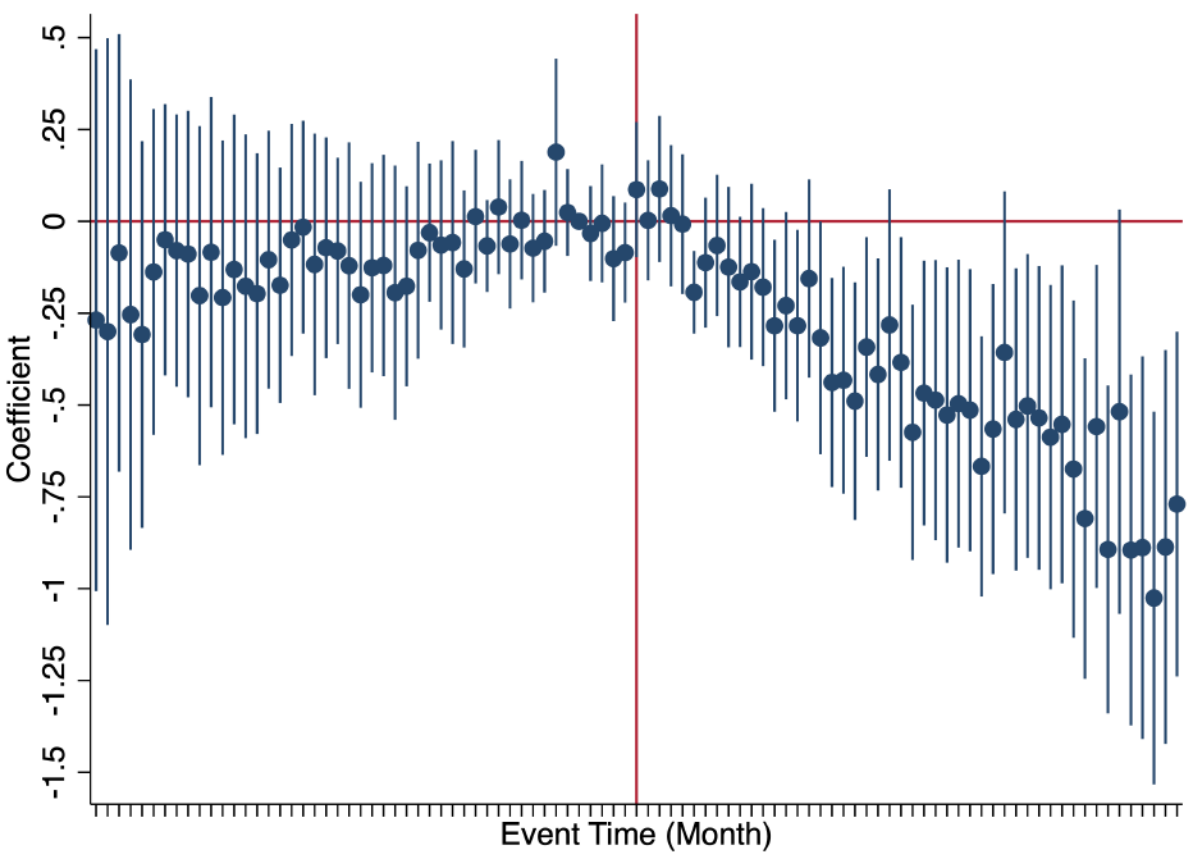


Figure A3. Goodman-Bacon Decomposition

This figure shows graphically the Goodman-Bacon decomposition of staggered difference-in-difference regression coefficient estimate (Goodman-Bacon, 2021). "Earlier Group Treatment vs. Later Group Comparison" is the effect measured comparing the states treated earlier to the states treated later. "Later Group Treatment vs. Earlier Group Comparison" is the effect measured comparing states treated later to states treated earlier. "Treatment vs. Never Treated" is the effect measured using states that are never treated as control firms for states that are treated. "Treatment vs. Already Treated" is the effect measured using states that are always treated during the sample period as controls for states treated during the sample period. The average treatment effects for the different comparison groups are shown in Table 5.

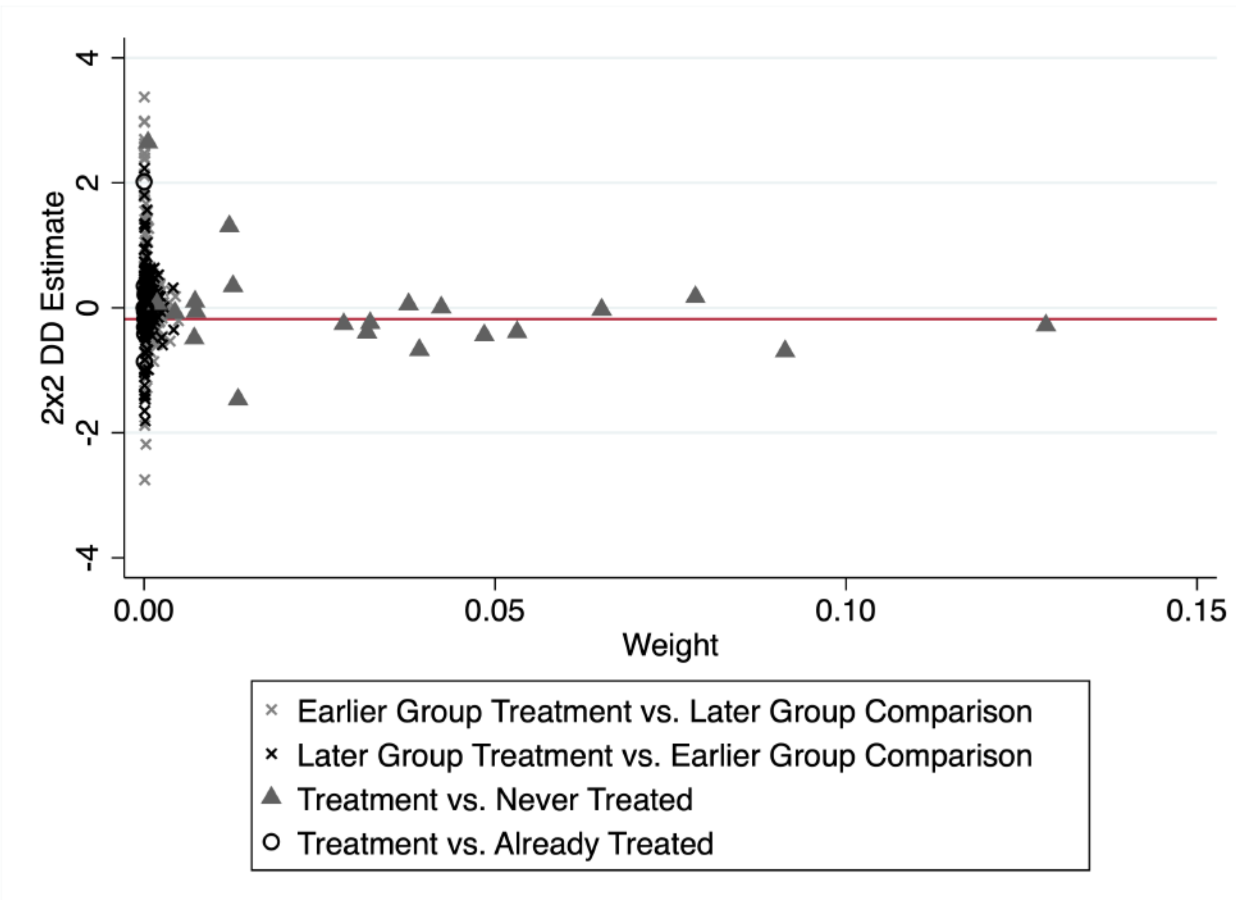
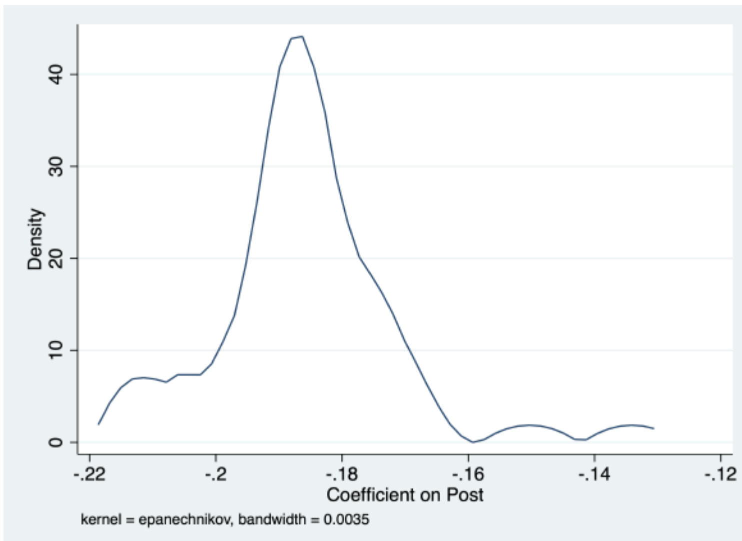


Figure A4. Main Effect Dropping Each State

This figure shows the distribution of the estimated policy effect in Table 4 Column (1) when dropping one state at a time. The y-axis is the fraction of the sample that has a coefficient that falls within a specific bin's range. The figure shows that the result is not driven by any one state.



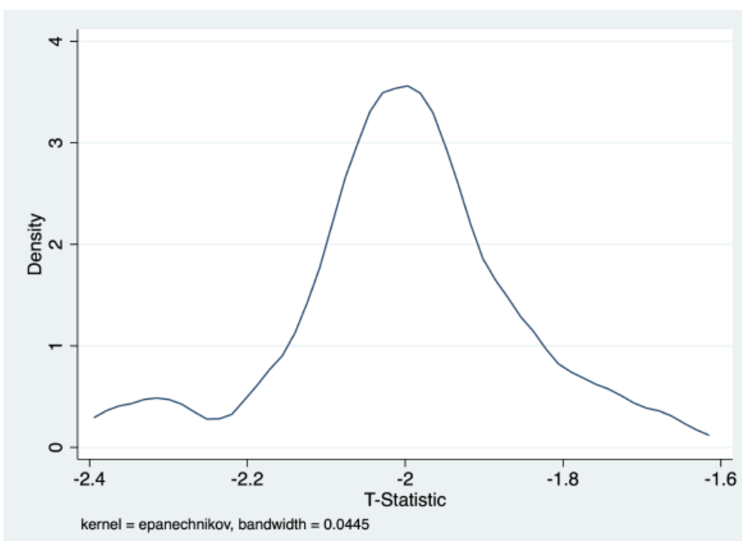


TABLE A1. Correlations

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 30 states that have adopted the Model Act by 2020, 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(s), 2 for the second earliest adopting state(s), 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 2020) 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 2020. In both panels, the following characteristics are measured at the state level as of December 2015, before the Model Act was finalized. *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. *Log State Population* is the natural logarithm of state population. *Average Credit Score* measures the average credit score of the elderly in a state. *Subprime 65+* is the proportion of elderly who are subprime in a state. *Low Income 65+* is the proportion of elderly who are low income in a state. *Age 65+* is the average age of the elderly in a state. *Male 65+* is the proportion of the elderly that are male in a state. *Married 65+* is the proportion of the elderly that are married in a state. *Average Household Income* is the average household income of the elderly in a state. *Debt-to-Income 65+* is the average debt-to-income ratio for the elderly in a state. *Bachelor or Higher* is the proportion of elderly who have at least a bachelors degree.

Panel A: Group of Adoption (1 = Earliest)				
	(1)	(2)	(3)	(4)
Number of Elder Exploitation Cases Per 1000	-10.067			-4.110
	(6.835)			(12.084)
Fraction of Population 65+		0.412		0.760
		(0.551)		(0.996)
Log State Population			0.984	-0.155
			(1.090)	(1.845)
Average Credit Score 65+				-0.331
				(1.047)
Subprime 65+				-46.301
				(223.770)
Low Income 65+				37.592
				(126.308)
Age 65+				2.706
				(3.342)
Male 65+				1.075
				(2.232)
Married 65+				0.133
				(0.700)
Average Household Income 65+				0.533
				(0.604)
Debt-to-Income 65+				0.556
				(4.696)
Bachelor or Higher 65+				-18.217
				(74.895)
R^2	0.07	0.02	0.03	0.27
# States	30	30	30	30

Panel B: Adoption Dummy (1=Adopted Model Act, 0=Not Adopted)				
	(1)	(2)	(3)	(4)
Number of Elder Exploitation Cases Per 1000	0.595			0.262
	(0.554)			(0.732)
Fraction of Population 65+		0.001		0.021
		(0.041)		(0.064)
Log State Population			-0.033	0.030
			(0.068)	(0.092)
Average Household Income 65+				-0.035
				(0.028)
Average Credit Score 65+				-0.042
				(0.057)
Subprime 65+				-10.592
				(12.972)
Low Income 65+				-5.272
				(6.445)
Age 65+				-0.150
				(0.210)
Male 65+				-0.036
				(0.135)
Married 65+				-0.003
				(0.035)
Debt-to-Income 65+				0.050
				(0.240)
Bachelor or Higher 65+				0.331
				(3.427)
R^2	0.02	0.00	0.00	0.16
# States	51	51	51	51

TABLE A3. Effect of NASAA's Model Act vs. FINRA's Rules 2165 and 4512

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 the year-month fixed effects. Standard errors clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Y = Elder Financial Exploitation Cases	
	(1)	(2)
Post	-0.186**	-0.205*
	(0.092)	(0.108)
Post × FINRA Passed		0.070
		(0.193)
Year-Month FE	Yes	Yes
County FE	Yes	Yes
County-Linear Trend	Yes	Yes
Controls	Yes	Yes
Adjusted R^2	0.67	0.67
# Counties	3139	3139
Observations	245169	245169

TABLE A4. Effects of Deputization on Elder Financial Exploitation at State-Month Level

This table presents DiD estimates of the effect of the deputizing financial professionals on elder financial exploitation. The outcome in Column (1) is the natural logarithm of one plus the number of elder financial exploitation cases in a county-month; Column (2) is an indicator variable that equals to one if a county-month has above zero elder financial exploitation cases; Columns (3) and (5) is the number of cases; and Column (4) is 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. Standard errors clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Y = Elder Financial Exploitation Cases				
	Y		Ln(1+# Elder Abuse Cases	Y/Pop. 65+	Y
	(1)	(2)	(3)	(4)	(5)
Post	-36.962*				
	(21.903)				
Pre 8		10.873	-0.059	0.220	-0.136
		(39.572)	(0.144)	(0.893)	(0.137)
Pre 7		11.836	-0.188	-0.126	-0.148
		(33.077)	(0.124)	(0.819)	(0.140)
Pre 6		8.838	-0.171	-0.481	-0.147
		(29.993)	(0.110)	(0.775)	(0.091)
Pre 5		4.726	-0.019	0.127	-0.092
		(26.768)	(0.105)	(0.723)	(0.079)
Pre 4		2.445	-0.012	0.304	-0.014
		(19.119)	(0.077)	(0.508)	(0.066)
Pre 3		4.937	-0.057	-0.180	-0.011
		(13.177)	(0.079)	(0.409)	(0.063)
Pre 2		2.763	0.025	0.254	-0.010
		(9.563)	(0.079)	(0.371)	(0.050)
Pre 1		.	.	.	.
Post 0		-8.912	-0.048	-0.364	-0.039
		(8.290)	(0.065)	(0.389)	(0.053)
Post 1		-34.302**	-0.137	-0.893*	-0.040
		(13.565)	(0.089)	(0.479)	(0.080)
Post 2		-28.738	-0.175*	-1.312*	-0.131
		(20.127)	(0.098)	(0.777)	(0.117)
Post 3		-48.384	-0.128	-0.609	-0.209
		(29.246)	(0.104)	(0.766)	(0.135)
Post 4		-63.755*	-0.189	-1.353	-0.242
		(34.491)	(0.131)	(0.859)	(0.152)
Post 5		-75.966*	-0.203*	-2.053**	-0.251*
		(40.550)	(0.114)	(0.877)	(0.133)
Post 6		-95.481**	-0.226*	-1.773*	-0.296**
		(45.470)	(0.134)	(1.015)	(0.147)
Post 7		-128.121***	-0.104	-1.991*	-0.291**
		(47.538)	(0.140)	(1.046)	(0.130)
Specification	OLS	OLS	OLS	OLS	Poisson
Year-Month FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
State-Linear Trend	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.81	0.82	0.89	0.75	.
Observations	3913	3913	3913	3913	3913

TABLE A5. Growth in Reporting from 2014 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 (2014 to 2016)* is the growth in elder abuse cases in a state from 2014 to 2016. In Column (1), if a state has not adopted the Model Act by the end of the sample (December 2020), then we assume the state adopted the Model Act in December 2020. 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)	-3.352	3.194
	(10.217)	(7.712)
Adjusted R^2	-0.02	-0.03
Observations	50	30

TABLE A6. Effects of Deputization on Elder Financial Exploitation for Different Sample Periods

For different start years, this table presents DiD 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 clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	# Elder Financial Exploitation Cases		
	(1)	(2)	(3)
Pre 8	-0.201	-0.507	-0.905
	(0.363)	(0.548)	(0.840)
Pre 7	-0.094	-0.153	-0.486
	(0.235)	(0.348)	(0.504)
Pre 6	-0.109	-0.244	-0.527
	(0.209)	(0.275)	(0.432)
Pre 5	-0.070	-0.124	-0.240
	(0.190)	(0.222)	(0.372)
Pre 4	-0.087	-0.110	-0.249
	(0.147)	(0.165)	(0.241)
Pre 3	-0.012	-0.009	-0.038
	(0.081)	(0.089)	(0.110)
Pre 2	0.034	0.032	0.038
	(0.044)	(0.046)	(0.057)
Pre 1	.	.	.
Post 0	-0.005	-0.004	0.024
	(0.064)	(0.067)	(0.075)
Post 1	-0.131	-0.122	-0.097
	(0.111)	(0.115)	(0.124)
Post 2	-0.277*	-0.262*	-0.227*
	(0.142)	(0.135)	(0.135)
Post 3	-0.381**	-0.356**	-0.302*
	(0.175)	(0.166)	(0.170)
Post 4	-0.485**	-0.458**	-0.397*
	(0.208)	(0.199)	(0.203)
Post 5	-0.469**	-0.442**	-0.384*
	(0.228)	(0.217)	(0.222)
Post 6	-0.611**	-0.578**	-0.512**
	(0.253)	(0.243)	(0.247)
Post 7	-0.728**	-0.693**	-0.637**
	(0.275)	(0.272)	(0.288)
Sample Years	≥2014	≥2015	≥2016
Year-Month FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
County-Linear Trend	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Adjusted R^2	0.63	0.65	0.67
# Counties	3139	3100	3100
Observations	245169	214451	181476

TABLE A7. Effects of Deputization on Elder Financial Exploitation for Different End Years

For different end years, this table presents DiD 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 clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	# Elder Financial Exploitation Cases)			
	(1)	(2)	(3)	(4)
Pre 8	-0.201	-0.113	0.091	0.065
	(0.363)	(0.301)	(0.179)	(0.182)
Pre 7	-0.094	-0.036	0.143	0.123
	(0.235)	(0.198)	(0.125)	(0.129)
Pre 6	-0.109	-0.064	0.103	0.087
	(0.209)	(0.178)	(0.113)	(0.116)
Pre 5	-0.070	-0.032	0.129	0.165
	(0.190)	(0.146)	(0.101)	(0.105)
Pre 4	-0.087	-0.056	0.118	0.090
	(0.147)	(0.130)	(0.074)	(0.074)
Pre 3	-0.012	0.010	0.110*	0.057
	(0.081)	(0.100)	(0.063)	(0.057)
Pre 2	0.034	0.062	0.043	0.034
	(0.044)	(0.079)	(0.045)	(0.041)
Pre 1	.	.	.	.
Post 0	-0.005	-0.145	-0.094*	-0.060
	(0.064)	(0.094)	(0.052)	(0.057)
Post 1	-0.131	-0.278**	-0.095	-0.107
	(0.111)	(0.122)	(0.060)	(0.099)
Post 2	-0.277*	-0.337**	-0.202**	-0.116
	(0.142)	(0.149)	(0.088)	(0.095)
Post 3	-0.381**	-0.375**	-0.281**	-0.254***
	(0.175)	(0.176)	(0.117)	(0.090)
Post 4	-0.485**	-0.555***	-0.307**	
	(0.208)	(0.197)	(0.119)	
Post 5	-0.469**	-0.524**		
	(0.228)	(0.214)		
Post 6	-0.611**			
	(0.253)			
Post 7	-0.728**			
	(0.275)			
Sample Years	≤2020	≤2019	≤2018	≤2017
Year-Month FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
County-Linear Trend	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.63	0.63	0.65	0.66
# Counties	3139	3100	3100	3100
Observations	245169	207774	172320	135828

TABLE A8. 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). 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 the year-month fixed effects. Standard errors clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	# Elder Financial Exploitation Cases		
Deputy =	Investment Advisers	Brokers	Pure Brokers
	(1)	(2)	(3)
Pre 8	-0.273	-0.385	-0.399
	(0.285)	(0.311)	(0.328)
Pre 8 × Deputy	0.221	0.118	0.070
	(0.320)	(0.351)	(0.339)
Pre 7	-0.194	-0.299	-0.309
	(0.191)	(0.209)	(0.220)
Pre 7 × Deputy	0.190	0.070	0.018
	(0.250)	(0.261)	(0.242)
Pre 6	-0.224	-0.316*	-0.321
	(0.164)	(0.182)	(0.193)
Pre 6 × Deputy	0.102	0.004	-0.032
	(0.230)	(0.243)	(0.228)
Pre 5	-0.136	-0.208	-0.212
	(0.160)	(0.177)	(0.187)
Pre 5 × Deputy	0.111	0.040	0.022
	(0.213)	(0.221)	(0.198)
Pre 4	-0.109	-0.161	-0.172
	(0.117)	(0.128)	(0.135)
Pre 4 × Deputy	0.197	0.146	0.109
	(0.155)	(0.154)	(0.135)
Pre 3	-0.031	-0.069	-0.078
	(0.078)	(0.082)	(0.082)
Pre 3 × Deputy	0.156	0.123	0.087
	(0.159)	(0.143)	(0.115)
Pre 2	0.029	0.011	0.006
	(0.052)	(0.054)	(0.052)
Pre 2 × Deputy	0.106	0.090	0.061
	(0.123)	(0.117)	(0.101)
Post 0	-0.034	-0.050	-0.048
	(0.069)	(0.071)	(0.075)
Post 0 × Deputy	-0.660***	-0.627***	-0.555***
	(0.101)	(0.105)	(0.102)
Post 1	-0.139	-0.150	-0.142
	(0.100)	(0.104)	(0.108)
Post 1 × Deputy	-0.897***	-0.830***	-0.713***
	(0.143)	(0.150)	(0.143)
Post 2	-0.168	-0.161	-0.159
	(0.132)	(0.140)	(0.144)
Post 2 × Deputy	-0.862***	-0.781***	-0.669***
	(0.132)	(0.141)	(0.141)
Post 3	-0.129	-0.096	-0.106
	(0.154)	(0.165)	(0.170)
Post 3 × Deputy	-0.724***	-0.610***	-0.504***
	(0.170)	(0.182)	(0.174)
Post 4	-0.169	-0.113	-0.127
	(0.181)	(0.195)	(0.201)
Post 4 × Deputy	-0.678***	-0.510**	-0.383*
	(0.186)	(0.198)	(0.192)
Post 5	-0.081	0.007	-0.022
	(0.189)	(0.206)	(0.216)
Post 5 × Deputy	-0.604***	-0.399*	-0.285
	(0.225)	(0.237)	(0.232)
Post 6	-0.201	-0.104	-0.134
	(0.208)	(0.224)	(0.236)
Post 6 × Deputy	-0.677***	-0.467*	-0.344
	(0.252)	(0.262)	(0.259)
Post 7	-0.372*	-0.260	-0.277
	(0.214)	(0.227)	(0.240)
Post 7 × Deputy	-0.623*	-0.336	-0.161
	(0.315)	(0.298)	(0.287)
Year-Month FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
County-Linear Trend	Yes	Yes	Yes
Interacted Controls	Yes	Yes	Yes
Adjusted R^2	0.67	0.67	0.66
# Counties	3139	3139	3139
Observations	245169	245169	245169

TABLE A9. Placebo

This table presents DiD 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 clustered by state 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	-0.002	0.000
	(0.004)	(0.001)
Year-Month FE	Yes	Yes
County FE	Yes	Yes
Adjusted R^2	0.36	0.56
# Counties	3139	3139
Observations	225333	225333

TABLE A10. Effects of Deputization on Elder Exploitation by Industry of Reporting Firm

This table presents the dynamic DiD estimates of the effect of the deputizing financial professionals on elder financial exploitation. The outcome in Column (1) is the number of cases in a county-month reported by depository institutions; the outcome in Column (2) is the number of cases reported by money services business; and the outcome in Column (3) is the number of cases reported by pure broker-dealers. Note that depository institutions include bank holding companies that may contain divisions providing investment advisery and broker-dealer services. The coefficients on *Pre #* and *Post #* estimate the dynamic effect of deputization over the six-months periods before and after the month financial professionals are deputized and thereby empowered to reach out to trusted contacts and halt suspicious transactions because a state adopts the Model Act. For example, *Post 0* is the effect of deputization in months $t = 0$ to $t = 5$, with $t = 0$ being the month of deputization. We omit *Pre 1*, the six months prior to deputization. Standard errors clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	# Depository Institution	# Money Services Business	# Securities
	(1)	(2)	(3)
Pre 8	-0.260	0.049	-0.031
	(0.381)	(0.099)	(0.030)
Pre 7	-0.152	0.051	-0.022
	(0.257)	(0.094)	(0.022)
Pre 6	-0.133	0.013	-0.025
	(0.229)	(0.086)	(0.028)
Pre 5	-0.089	0.004	-0.025
	(0.184)	(0.037)	(0.019)
Pre 4	-0.070	-0.008	-0.022
	(0.138)	(0.037)	(0.019)
Pre 3	-0.030	0.022	-0.024
	(0.077)	(0.030)	(0.017)
Pre 2	0.019	0.003	-0.021
	(0.039)	(0.024)	(0.016)
Pre 2	0.019	0.003	-0.021
	(0.039)	(0.024)	(0.016)
Pre 1	.	.	.
Post 1	-0.163	0.059	0.023
	(0.111)	(0.039)	(0.022)
Post 2	-0.330**	0.052	-0.006
	(0.144)	(0.039)	(0.021)
Post 3	-0.401**	0.052	-0.035**
	(0.181)	(0.051)	(0.016)
Post 4	-0.534**	0.070	-0.034
	(0.211)	(0.046)	(0.021)
Post 5	-0.511**	0.065	-0.055**
	(0.231)	(0.046)	(0.024)
Post 6	-0.655**	0.078*	-0.059
	(0.251)	(0.046)	(0.037)
Post 7	-0.810***	0.081*	-0.050
	(0.288)	(0.046)	(0.049)
Year-Month FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
County-Linear Trend	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Adjusted R^2	0.58	0.36	0.37
# Counties	3139	3139	3139
Observations	245169	245169	245169

TABLE A11. 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 clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	# Elder Financial Exploitation Cases		
	(1)	(2)	(3)
Per Capita Investment Advisers	0.369**		-0.377**
	(0.149)		(0.158)
Per Capita Brokers		0.514***	0.815***
		(0.158)	(0.202)
Constant	1.049***	1.044***	1.048***
	(0.086)	(0.084)	(0.083)
Year-Month FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Adjusted R^2	0.34	0.35	0.35
# Counties	3139	3139	3139

TABLE A12. Effects of Deputization on Elder Financial Exploitation in Counties with No Advisers and No Brokers

This table presents DiD estimates of the effect of the deputizing financial professionals on elder financial exploitation. The outcome in Column (1) is the natural logarithm of one plus the number of elder financial exploitation cases in a county-month; Column (2) is an indicator variable that equals to one if a county-month has above zero elder financial exploitation cases; Columns (3) and (5) is the number of cases; and Column (4) is 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. Standard errors clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Elder Financial Exploitation Cases	
	(1)	(2)
Post	0.071	
	(0.046)	
Pre 8		-0.007
		(0.048)
Pre 7		0.029
		(0.044)
Pre 6		0.025
		(0.048)
Pre 5		0.042
		(0.051)
Pre 4		0.032
		(0.046)
Pre 3		0.052
		(0.047)
Pre 2		0.096
		(0.067)
Pre 1		.
		.
Post 0		0.087
		(0.089)
Post 1		0.096
		(0.061)
Post 2		0.072
		(0.068)
Post 3		0.118
		(0.075)
Post 4		0.101
		(0.061)
Post 5		0.112
		(0.085)
Post 6		0.039
		(0.072)
Post 7		-0.008
		(0.120)
Year-Month FE	Yes	Yes
County FE	Yes	Yes
County-Linear Trend	Yes	Yes
Controls	Yes	Yes
Adjusted R^2	0.78	0.78
# Counties	2997	2997
Observations	59245	59245

TABLE A13. Effect by Activity

This table presents DiD 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 clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	# Elder Financial Exploitation Cases of Type X					
X=	Fund Transfers	Personal Checks	Cashier Check	Debit Card	Deposit Account	Credit Card
	(1)	(2)	(3)	(4)	(5)	(6)
Pre 8	-0.318	-0.184	-0.141	-0.142	-0.811	-0.051
	(0.409)	(0.211)	(0.120)	(0.221)	(0.755)	(0.082)
Pre 7	-0.210	-0.129	-0.105	-0.035	-0.670	-0.045
	(0.272)	(0.155)	(0.085)	(0.111)	(0.599)	(0.064)
Pre 6	-0.182	-0.128	-0.101	-0.059	-0.630	-0.026
	(0.242)	(0.144)	(0.084)	(0.108)	(0.564)	(0.056)
Pre 5	-0.149	-0.102	-0.091	-0.079	-0.601	0.005
	(0.181)	(0.117)	(0.072)	(0.089)	(0.510)	(0.039)
Pre 4	-0.154	-0.108	-0.075	-0.088	-0.592	-0.000
	(0.160)	(0.114)	(0.062)	(0.087)	(0.471)	(0.036)
Pre 3	-0.079	-0.070	-0.048	-0.042	-0.380	-0.018
	(0.088)	(0.076)	(0.039)	(0.050)	(0.339)	(0.032)
Pre 2	-0.049	-0.018	-0.021	-0.035	-0.086	-0.023
	(0.058)	(0.028)	(0.015)	(0.030)	(0.076)	(0.037)
Pre 1	.	.	.	.	.	.
Post 0	0.061	0.004	-0.005	-0.019	0.113	0.005
	(0.086)	(0.030)	(0.012)	(0.033)	(0.116)	(0.025)
Post 1	0.146	-0.047	-0.027	-0.038	0.089	-0.062
	(0.270)	(0.056)	(0.027)	(0.056)	(0.338)	(0.068)
Post 2	-0.202**	-0.163**	-0.080*	-0.150**	-0.483*	-0.039
	(0.099)	(0.078)	(0.044)	(0.067)	(0.257)	(0.057)
Post 3	-0.343***	-0.234**	-0.103*	-0.214***	-0.772**	-0.099
	(0.126)	(0.097)	(0.055)	(0.078)	(0.342)	(0.060)
Post 4	-0.456**	-0.269**	-0.130**	-0.261***	-1.018**	-0.109
	(0.174)	(0.112)	(0.062)	(0.093)	(0.418)	(0.068)
Post 5	-0.519**	-0.287**	-0.142**	-0.260***	-1.112**	-0.140**
	(0.197)	(0.125)	(0.066)	(0.094)	(0.468)	(0.056)
Post 6	-0.687**	-0.352**	-0.178**	-0.355***	-1.390**	-0.112**
	(0.262)	(0.132)	(0.067)	(0.115)	(0.537)	(0.048)
Post 7	-0.724**	-0.449***	-0.238***	-0.464***	-1.714***	-0.052
	(0.272)	(0.139)	(0.072)	(0.128)	(0.543)	(0.109)
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Linear Trend	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.49	0.53	0.44	0.61	0.35	0.51
# Counties	3139	3139	3139	3139	3139	3139
Observations	245169	245169	245169	245169	245169	245169

TABLE A14. 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 clustered by state are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
	I(Regulatory Actions)	
Post	0.00019	
	(0.00044)	
Pre 8		-0.00035
		(0.00103)
Pre 7		-0.00014
		(0.00089)
Pre 6		0.00021
		(0.00114)
Pre 5		-0.00070
		(0.00081)
Pre 4		-0.00009
		(0.00080)
Pre 3		0.00137**
		(0.00068)
Pre 2		0.00151
		(0.00093)
Post 0		0.00051
		(0.00047)
Post 1		0.00103
		(0.00079)
Post 2		0.00047
		(0.00054)
Post 3		0.00123
		(0.00090)
Post 4		0.00068
		(0.00082)
Post 5		0.00032
		(0.00097)
Post 6		0.00148
		(0.00139)
Post 7		0.00048
		(0.00104)
Constant	-0.00063	-0.00074
	(0.00351)	(0.00346)
Controls	Yes	Yes
Year-Month FE	Yes	Yes
County FE	Yes	Yes
Adjusted R^2	0.04	0.04
# Counties	2812	2812
Observations	183796	183796

TABLE A15. 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